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Research Article

Optimizing Transportation Network of Recovering End-of-Life Vehicles by Compromising Program in Polymorphic Uncertain Environment

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With rapid development of technology and improvement of living standards, the per capita holding of automobiles greatly increases, and the amount of end-of-life vehicles (ELVs) becomes larger and larger such that it is valuable to investigate an effective strategy for recycling ELVs from the viewpoints of environmental protection and resource utilization. In this paper, an optimization model with fuzzy and stochastic parameters is built to formulate the transportation planning problems of recycling ELVs in polymorphic uncertain environment, where the unit processing and transportation costs, the selling price of reused items, and the fixed cost are all fuzzy, while the demand in secondary market and the production capacity are random owing to features underlying the practical data. For this complicated polymorphic uncertain optimization model, a unified compromising approach is proposed to hedge the uncertainty of this model such that some powerful optimization algorithms can be applied to make an optimal recycling plan. Then, an interactive algorithm is developed to find a compromising solution of the uncertain model. Numerical results show efficiency of the algorithm and a number of important managerial insights are revealed from the proposed model by scenario analysis and sensitivity analysis.

1. Introduction

1.1. Background. With rapid development of technology and improvement of living standards, the per capita holding of automobiles greatly increases. In China, as the largest developing country with a population of around 1.3 billion, huge amount of end-of-life vehicles (ELVs) is bringing enormous pressure on its environment and human life. Actually, the civilian car ownership in China has reached 137 million in 2013, and has been almost doubling every four years. If the average lifespan of a car is 8-9 years, then the number of ELVs will exceed 14 million in 2020 [1]. In the world, it is estimated that the number of vehicles will rise to 1.85 billion by 2030, and the scrap generated from the ELVs will be 3.71 billion tonnes [2]. In an era of resources shortage and environmental deterioration, recycling the ELVs can give birth to new-style industry as a typical low-carbon and sustainable production approach [3, 4].

It is well known that the ELVs contain a great amount of reusable components and materials such as steel, copper, rubber, etc. Therefore, recycling the ELVs offer considerable economic and environmental benefits [5]. This fact has been paid great attention either by governments, by industry or by academia. Actually, the European Union (EU) has established legal regulation that manufacturers are responsible for take-back of ELVs from end-users, dismantling, shredding, and recycling of ELVs [6]. Directive 2000/53/EC required that, no later than 1 January 2015, for all the ELVs, the reuse and recovery rate shall be increased to a minimum of 95% by an average weight per vehicle and year. Within the same time limit, the reuse and recycling rate shall be increased to a minimum of 85% by an average weight per vehicle and year. Japan had an ELV recovery rate of 85% in 2002, its attained target reached 95% by 2015 [7].

In China, a series of relevant policies and regulations have been issued to improve the management mechanism for the ELV recycling industry since 2001. The "automotive products recycling technology policy" was implemented in 2006, which specifies utilization rate targets of the recyclable products in China [8]. The established China automotive material data system (CAMDS) in 2009 has played an important role in implementing the automotive products recyclable rate and the managing the ELVs. Chinese government has legislated that "yellow label cars" (heavily polluting vehicles) must be eliminated by 2017 [3]. Automotive components remanufacturing, as an essential part in automotive life-cycle development, has become a prominent direction to promote sustainable planning of automobile industry in China [9]. Actually, these policies are bringing a great of economic and environmental benefits to China.

1.2. Literature Review. In recent years, recovery of used products has become increasingly important owing to economic reasons and growing environmental or legislative concern [10]. Particularly, the ELV recycling plays an important role for sustainable development. For example, each remanufactured engine could save 68-83% of the energy required to manufacture a new engine, and decrease carbon dioxide emissions by 73-87%. The coolants and batteries in ELVs can also be recycled, and it reduces emissions of greenhouse gases and gases that lead to acidification. The main ingredient of coolant is Solid CO_2, and the electrolyte of lead accumulator is lead accumulator [1]. Recycling metals from the ELVs could decrease the amounts of resources consumed building new cars. If all the vehicle materials can be recycled to produce new vehicles, about 30% of the energy consumption can be saved [11].

Summarily, the ELVs contain a great quantity of reusable components and materials such as steel, copper, rubber, plastics, etc. which can be reused or remanufactured. Thus, the remanufacturing industry of ELVs necessarily has strategic significance as it better utilizes resources and creates higher values. Especially, recycling ELVs can play an important role in realizing the country's sustainable development goals. In 2003, China has introduced extended producer responsibility (EPR), which requires that any manufacturer should participate in ELV take-back, dismantling, remanufacturing, and so on [12]. The "automotive product recycling technology policy" in China requires carmakers to improve the design of vehicles, spare parts, and raw materials, as well as reduce the use of lead and other environmentally hazardous substances. Actually, this policy is an encouragement to the carmakers such that more recycled materials from the ELVs are used [13].

It is easy to see that recycling the ELVs depends on establishment of an efficient ELV recycling network, which not only can reduce the impact on the environment during the recycling process, but also can facilitate the effective reuse of recycled resources [14]. Furthermore, construction of optimization models for production planning problems of recycling the ELVs is helpful to provide the decision-makers an optimal plan for the practical operation of the recycling system [15].

In this connection, Cruz-Rivera et al. developed a reverse logistics network design for collection of the ELVs in Mexico [16]. Demirel et al. proposed a deterministic mixed integer linear programming (MILP) model for the ELV recycling network design, where all of the end-users, collection centers, dismantlers, shredders, landfills, recycling facilities, and secondary markets are included [6]. On the basis of [6], Demirel et al. in 2017 developed a closed-loop supply chain for the ELVs recycling, where some reusable components after processing are sold to suppliers for remanufacturing [17]. Finally, new vehicles with the remanufactured components will flow to consumers. Ene et al. considered refurbishment in ELVs recycling network; the reusable parts must be refurbished before they could be sold to secondary markets [18]. Phuc et al. designed inspection centers in the ELVs recycling system; those ELVs passing inspection is repaired in the repair centers and then is sold to the used vehicle markets [19]. Additionally, in [2], municipal solid waste incinerator and advanced thermal treatment measures are applied to dispose autoshredder residue (ASR) besides landfilling.

In some of the existing models for recycling the ELVs, various kinds of uncertainties have also been considered. It suggests in [20] that uncertainty seems to be the key factor influencing the management of ELVs. Özkır et al. stated that the selling price of products can be described by trapezoidal fuzzy sets such that both seller's and buyer's satisfaction levels are reflected [21]. In [19], the fixed cost, the transportation cost and the processing cost were also regarded as trapezoidal fuzzy sets in a reverse ELV recovery network. In [22], the capacities of sorting entities for recycling the ELVs were observed as random parameters, while the procurement cost, the transportation cost, the processing cost, and the storage cost were assumed to be interval parameters. In a global supply chain management model proposed by Wan et al., the demand of products for retailers is assumed to be stochastic and depends on the price of products [23].

Very recently, a polymorphic uncertain equilibrium model (PUEM) was developed by Wan et al. for the problem of decentralized supply chain management, where the demand of consumers was regarded as a continuous random variable, and the holding cost of the retailer and the transaction cost between the manufacturer and retailer were described by fuzzy sets [24]. Then, for the PUEM, a deterministic equivalent formulation (DEF) was first derived by compromise programming approach such that the existing powerful algorithms in the standard smooth optimization were employed to find an approximate equilibrium point for the uncertain problem. It is also noted that there are many different approaches to removing uncertainty in the uncertain model. For example, expectation method was applied in [19] to deal with the fuzzy objective such that the fuzzy objective can be converted into a deterministic one. Chance-constrained programming method was adopted in [22] to deal with the random constraints.

However, in the existing results for optimizing the system of recycling the ELVs, there are still some deficiencies, which can be briefly summarized as follows.

(1) Polymorphic uncertainty is rarely considered in this special reverse logistics network. Especially, randomness of

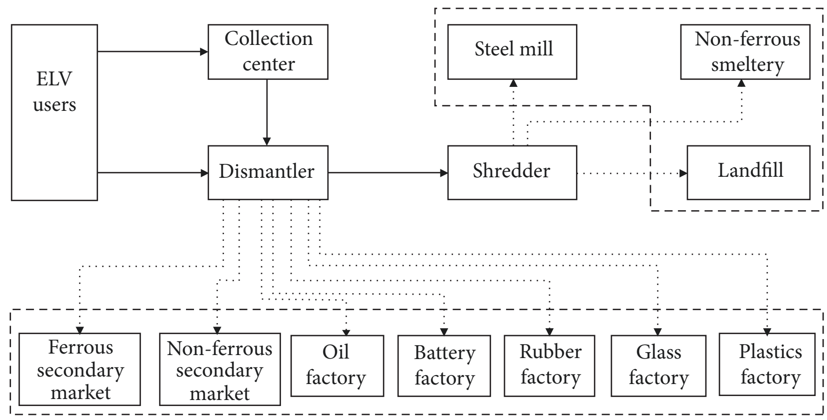


Figure 1: Structure of the ELV recovery network.

the demand in the secondary markets of reusable components has not been taken account into design of an optimal ELV recovery network.

(2) To hedge fuzziness of the objective function, the expectation method is often applied to transform the fuzzy objective into a deterministic one. Clearly, this method can not address the feature of variance in a fuzzy set. A more reasonable method should capture all information in a fuzzy objective function, which includes the lower and upper variances of a fuzzy set, as well as its center value.

1.3. Motivation of This Research. From the above literature review, it is necessary to build a new polymorphic uncertain optimization model for a more efficient system of the ELV recovery management. In particular, this model should simultaneously capture fuzziness and randomness of model parameters in a ELV recovery network design. Then, as done in [24], a unified compromising programming approach should be presented to convert the PUOM into a deterministic one such that the existing powerful optimization algorithms can be applied to find an approximately optimal strategy for recycling the ELVs.

In this paper, just like the mentioned reasons in [19, 21, 23, 24], we suppose that all of the fixed cost, the unit transportation cost, the unit processing cost, and the unit selling price of reused parts are fuzzy model parameters, and both of the capacity and the demand are regarded to be random variables. Then, our investigation proceeds along the following three subsequent steps.

Step 1. In a polymorphic uncertain environment, we construct a new optimization model to formulate the production planning problems of ELV recovery system.

Step 2. To hedge uncertainty of the model, a unified compromising programming approach will be proposed, which is associated with the following two phases: (1) in the first phase, the original problem is converted into an auxiliary crisp multiple-objective mixed integer linear programming problem; (2) in the second phase, a novel interactive fuzzy programming approach is proposed to find a preferred compromising solution through an interaction between the decision-maker with preference and the rational model [25].

Step 3. To answer what is the practical significance of the new model and the developed algorithm in this paper, we will reveal some important managerial insights from the proposed model by scenario analysis and sensitivity analysis.

The rest of the paper is organized as follows. Next section is devoted to the description of problem and construction of model. In Section 3, an interactive algorithm is developed. In Section 4, numerical results of case study are reported. In Section 5, sensitivity analysis is conducted, and some practical managerial implications are revealed from the constructed model. Some conclusions and suggestions on future research are presented in the last section.

2. Problem Description and Formulation

2.1. Problem Description. Similar to the setting in [6], the network structure of ELV recovery system to be addressed in this paper is shown in Figure 1.

As shown in Figure 1, the network nodes basically consist of the ELV sources such as the last owners, insurance companies and abandoned vehicles, the collection centers, the dismantlers, the shredders, the recycling facilities, the secondary markets, and the landfills.

Specifically, the process flow of the recycling network can be stated as follows. All of the ELVs must be treated in formal dismantling companies. The collection centers or dismantlers first procure the ELVs from the ELV sources. Then, the ELVs in the collection centers will all be transported to the dismantlers. In the dismantlers, it is first required to remove and store separately the fuel, the motor oil, the oil from transmission system, the hydraulic oil, the cooling liquid, the liquid from the brake system, and other liquids and hazardous substances if any. Subsequently, the components or materials removed from the scrap car are considered for reuse and recycling. Reusable ferrous and nonferrous components are sold to the secondary market, while the recycling materials, such as batteries, tyres, glass, plastics, and waste oil, are sold to the recycling factories. The remaining hulks are shipped to the shredders for further recycling. In the shredders, some materials can be mechanically recycled by shredder, air suction, magnetic sorters, and eddy current sorters. Finally, the hulks are divided into ferrous material, nonferrous material, and autoshredder residue (ASR). The sorted metals will be allocated to steel mills or nonferrous smelteries for further recycling, while ASR will be directly transported to the landfill.

In the recycling network in [6], all of the end-users, collection centers, dismantlers, shredders, landfills, recycling facilities, and secondary markets are the nodes of this network, and it is assumed that the last owners must return their vehicles to one of the collection centers or dismantlers. Different from the network in [6], Figure 1 indicates that (1) only ferrous and nonferrous components for reusing are sold to the secondary markets in our network; (2) there is no need to build the recycling facilities for processing the battery, tyre, glass, and plastics; instead, all of them are separately sold to the existent factories which have equipment for recycling; (3) our network is more in accordance with the suggested recycling system in China by [26, 27].

The goal of this paper is to formulate the above recycling network such that the total recycling cost is minimized, which is associated with the costs of transportation, processing, disposal, and the fixed opening costs in a multistage production plan. In order to build an optimization model that is more realistic than those available in the literature, uncertainty in recycling system must be incorporated into construction of model. Actually, due to incompleteness and unavailability of desired data, it is inappropriate to assume that the fixed opening cost, the unit transportation cost, the unit processing cost, the unit selling price of reconditioned parts, the capacity, and demand are all fixed constants. An acceptable approach is to describe these parameters by uncertain mathematical concepts from the theory of stochastic or fuzzy mathematics. Especially, in this paper, we assume that the fixed opening cost, the unit transportation cost, the unit processing cost, and the unit selling price of reconditioned parts are fuzzy sets, and the capacity levels of dismantlers, shredders, landfills, and the demand of secondary markets are random variables.

For simplicity, we suppose that the membership function of the relevant fuzzy sets is subject to possibility distribution (see Figure 2). Mathematically, any trapezoidal fuzzy number $\widetilde{c}$ is given by a membership function $\mu_{\widetilde{c}} : R \longrightarrow [0,1]$, where for any c,

$$\mu_{\widetilde{c}}(c) = \begin{cases} 0, & c \le c^p, \\ \dfrac{c - c^p}{c^{m_1} - c^p}, & c^p \le c \le c^{m_1}, \\ 1, & c^{m_1} \le c \le c^{m_2}, \\ \dfrac{c^0 - c}{c^0 - c^{m_2}}, & c^{m_2} \le c \le c^o, \\ 0, & c \ge c^o, \end{cases} \tag{1}$$

c^p, c^{m_1}, c^{m_2}, and c^o are given constants. Different values of c^p, c^{m_1}, c^{m_2}, and c^o define various fuzzy sets. From this viewpoint, any fuzzy number can be denoted by a quaternion $\widetilde{c} = (c^p, c^{m_1}, c^{m_2}, c^o)$. For fuzzy number $\widetilde{c}$, we call $(c^{m_1} - c^p)$ its the upper variance, call $(c^o - c^{m_2})$ its lower variance, and $(c^{m_1} + c^{m_2})$ the center value.

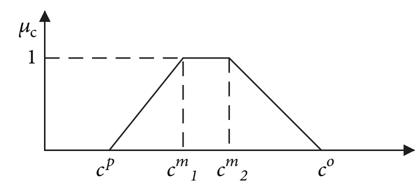


Figure 2: The trapezoidal possibility distribution of fuzzy number $\widetilde{c}$.

2.2. Notations. Before construction of model, we first introduce the following notations for readability.

Indexes

i: the labels of ELV sources, $i = 1, 2, \ldots, I$.

j: the labels of collection centers, $j = 1, 2, \ldots, J$.

k: the labels of dismantlers, $k = 1, 2, \ldots, K$.

l: the labels of shredders, $l = 1, 2, \ldots, L$.

s: the labels of secondary markets, $s = 1, 2, \ldots, S$.

m: the labels of steel mills, $m = 1, 2, \ldots, M$.

n: the labels of nonferrous smelteries, $n = 1, 2, \ldots, N$.

p: the labels of oil recycling factories, $p = 1, 2, \ldots, P$.

q: the labels of battery recycling factories, $q = 1, 2, \ldots, Q$.

r: the labels of rubber recycling factories, $r = 1, 2, \ldots, R$.

v: the labels of glass recycling factories, $v = 1, 2, \ldots, V$.

w: the labels of plastics recycling factories, $w = 1, 2, \ldots, W$.

u: the labels of landfills, $u = 1, 2, \ldots, U$.

t: the processing periods, $t = 1, 2, \ldots, T$.

Parameters

R_{it}: the amount of ELVs returned from ELV source i in period t (ton).

$\widetilde{f}_{kt}$: the fixed opening cost for dismantler k in period t (yuan).

$\widetilde{f}_{lt}$: the fixed opening cost for shredder l in period t (yuan).

$\widetilde{pc}_{kt}$: the unit cost of dismantling at dismantler k in period t (yuan/ton).

$\widetilde{pc}_{lt}$: the unit cost of shredding at shredder l in period t (yuan/ton).

$\widetilde{pc}_{ut}$: the unit cost of disposal at landfill u in period t (yuan/ton).

$\widetilde{s}_{1t}$: the unit price of selling of dismantler for ferrous components for reusing in period t (yuan/ton).

$\widetilde{s}_{2t}$: the unit price of selling of dismantler for nonferrous components for reusing in period t (yuan/ton).

$\widetilde{s}_{3t}$: the unit price of selling of dismantler for oil for recycling in period t (yuan/ton).

$\widetilde{s}_{4t}$: the unit price of selling of dismantler for battery for recycling in period t (yuan/ton).

$\widetilde{s}_{5t}$: the unit price of selling of dismantler for tyre for recycling in period t (yuan/ton).

$\widetilde{s}_{6t}$: the unit price of selling of dismantler for glass for recycling in period t (yuan/ton).

$\widetilde{s}_{7t}$: the unit price of selling of dismantler for plastics for recycling in period t (yuan/ton).

$\widetilde{z}_{1t}$: the unit price of selling of shredder for ferrous material for recycling in period t (yuan/ton).

$\widetilde{z}_{2t}$: the unit price of selling of shredder for nonferrous material for recycling in period t (yuan/ton).

$\widetilde{tc}_{ijt}$: the unit cost of transportation between ELV source i and collection center j for ELV in period t (yuan/ton·km).

$\widetilde{tc}_{ikt}$: the unit cost of transportation between ELV source i and dismantler k for ELV in period t (yuan/ton·km).

$\widetilde{tc}_{jkt}$: the unit cost of transportation between collection center j and dismantler k for ELV in period t (yuan/ton·km).

$\widetilde{tc}_{klt}$: the unit cost of transportation between dismantler k and shredder l for hulk in period t (yuan/ton·km).

$\widetilde{tc}_{lut}$: the unit cost of transportation between shredder l and landfill u for ASR in period t (yuan/ton·km).

d_{ij}: the distance between ELV source i and collection center j (km).

d_{ik}: the distance between ELV source i and dismantler k (km).

d_{jk}: the distance between collection center j and dismantler k (km).

d_{kl}: the distance between dismantler k and shredder l (km).

d_{lu}: the distance between shredder l and landfill u (km).

$\widehat{ca}_{jt}$: the capacity of collection center j in period t (ton).

$\widehat{ca}_{kt}$: the capacity of dismantler k in period t (ton).

$\widehat{ca}_{lt}$: the capacity of shredder l in period t (ton).

$\widehat{ca}_{ut}$: the capacity of landfill u in period t (ton).

$\widehat{de}_{1st}$: the demand of secondary market s for reusable ferrous components in period t (ton).

$\widehat{de}_{1st}$: the demand of secondary market s for reusable nonferrous components in period t (ton).

α: the weight percentage of hulk in ELV.

β_1: the weight percentage of reusable ferrous components in ELV.

β_2: the weight percentage of reusable nonferrous components in ELV.

β_3: the weight percentage of oil in ELV.

β_4: the weight percentage of batteries in ELV.

β_5: the weight percentage of tyres in ELV.

β_6: the weight percentage of glass in ELV.

β_7: the weight percentage of plastics in ELV.

η: the weight percentage of ASR in hulk.

η_1: the weight percentage of ferrous material in hulk.

η_2: the weight percentage of nonferrous material in hulk.

Decision Variables

B_{ijt}: the amount of ELVs transported from ELV source i to collection center j in period t.

C_{ikt}: the amount of ELVs transported from ELV source i to dismantler k in period t.

D_{jkt}: the amount of ELVs transported from collection center j to dismantler k in period t.

E_{klt}: the amount of hulk transported from dismantler k to shredder l in period t.

F_{lut}: the amount of ASR transported from shredder l to landfill u in period t.

$Q1_{kst}$: the amount of ferrous components transported from dismantler k to secondary market s in period t.

$Q2_{kst}$: the amount of nonferrous components transported from dismantler k to secondary market s in period t.

$Q3_{kpt}$: the amount of oil transported from dismantler k to oil recycling factory p in period t.

$Q4_{kqt}$: the amount of batteries transported from dismantler k to battery recycling factory q in period t.

$Q5_{krt}$: the amount of tyres transported from dismantler k to rubber recycling factory r in period t.

$Q6_{kvt}$: the amount of glass transported from dismantler k to glass recycling factory v in period t.

$Q7_{kwt}$: the amount of plastics transported from dismantler k to plastics recycling factory w in period t.

$Q8_{lmt}$: the amount of ferrous material transported from shredder l to steel mill m in period t.

$Q9_{lnt}$: the amount of nonferrous material transported from shredder l to nonferrous smeltery n in period t.

O_{kt}: if dismantler k is opened in period t, $O_{kt} = 1$; otherwise, $O_{kt} = 0$.

O_{lt}: if shredder l is opened in period t, $O_{lt} = 1$; otherwise, $O_{lt} = 0$.

2.3. Construction of Model for the ELV Recycling. We now formulate the objective function of the ELV recovery system in a centralized decision-making mode, being referred as to $\widetilde{\pi}$. The objective is to minimize the total cost of recycling system. It is associated with the fixed opening cost, the transportation cost, the processing cost, and the revenue from the sale income of the recycled resources. Therefore, the total cost function is written as

$$\widetilde{\pi} = \widetilde{FC} + \widetilde{PC} + \widetilde{TC} - \widetilde{RE}, \tag{2}$$

where the total fixed opening cost is

$$\widetilde{FC} = \sum_k \sum_t \widetilde{f}_{kt} O_{kt} + \sum_l \sum_t \widetilde{f}_{lt} O_{lt}, \tag{3}$$

the total transportation cost on each arc of the network reads

$$\begin{aligned} \widetilde{TC} = {} & \sum_i \sum_j \sum_t \widetilde{tc}_{ijt} B_{ijt} d_{ij} + \sum_i \sum_k \sum_t \widetilde{tc}_{ikt} C_{ikt} d_{ik} \\ & + \sum_j \sum_k \sum_t \widetilde{tc}_{jkt} D_{jkt} d_{jk} + \sum_k \sum_l \sum_t \widetilde{tc}_{klt} E_{klt} d_{kl} \\ & + \sum_l \sum_u \sum_t \widetilde{tc}_{lut} F_{lut} d_{lu} \\ & + \sum_k \sum_s \sum_t \widetilde{tc}_{kst} d_{ks} \left(Q1_{kst} + Q2_{kst} \right) \\ & + \sum_k \sum_p \sum_t \widetilde{tc}_{kpt} Q3_{kpt} d_{kp} \\ & + \sum_k \sum_q \sum_t \widetilde{tc}_{kqt} Q4_{kqt} d_{kq} \\ & + \sum_k \sum_r \sum_t \widetilde{tc}_{krt} Q5_{krt} d_{kr} \\ & + \sum_k \sum_v \sum_t \widetilde{tc}_{kvt} Q6_{kvt} d_{kv} \\ & + \sum_k \sum_w \sum_t \widetilde{tc}_{kwt} Q7_{kwt} d_{kw} \\ & + \sum_l \sum_m \sum_t \widetilde{tc}_{lmt} Q8_{lmt} d_{lm} \\ & + \sum_l \sum_n \sum_t \widetilde{tc}_{lnt} Q9_{lnt} d_{ln}, \end{aligned} \tag{4}$$

the total processing cost of dismantlers, shredders, and landfills is

$$\begin{aligned} \widetilde{PC} = {} & \sum_i \sum_k \sum_t \widetilde{pc}_{kt} C_{ikt} + \sum_j \sum_k \sum_t \widetilde{pc}_{kt} D_{jkt} \\ & + \sum_k \sum_l \sum_t \widetilde{pc}_{lt} E_{klt} + \sum_l \sum_u \sum_t \widetilde{pc}_{ut} F_{lut}, \end{aligned} \tag{5}$$

and the income from the sale of isolated materials is

$$\begin{aligned} \widetilde{RE} = {} & \sum_k \sum_s \sum_t \left(\widetilde{s}_{1t} Q1_{kst} + \widetilde{s}_{2t} Q2_{kst} \right) \\ & + \sum_k \sum_p \sum_t \widetilde{s}_{3t} Q3_{kpt} + \sum_k \sum_q \sum_t \widetilde{s}_{4t} Q4_{kqt} \\ & + \sum_k \sum_r \sum_t \widetilde{s}_{5t} Q5_{krt} + \sum_k \sum_v \sum_t \widetilde{s}_{6t} Q6_{kvt} \\ & + \sum_k \sum_w \sum_t \widetilde{s}_{7t} Q7_{kwt} + \sum_l \sum_m \sum_t \widetilde{z}_{1t} Q8_{lmt} \\ & + \sum_l \sum_n \sum_t \widetilde{z}_{2t} Q9_{lnt}. \end{aligned} \tag{6}$$

Remark 1. Note that, in (3), (4), (5), and (6), the opening cost, the unit transportation cost, the unit sale prices of all the reused components from the ELVs, and the unit processing cost for dismantling, shredding, and disposal at landfill are all supposed to be fuzzy model parameters. The advantage of this assumption is that these fuzzy parameters can reflect uncertain information of cost or revenue which can not be precisely calculated by statistical (financial) data. Actually, it is often that depreciation degree of the production tools can only be described as higher or lower, and market reputation of the reused products can only be said to be more credible. A fuzzy set is the most appropriate mathematical concept to characterize these uncertain language evaluations such as high, low, and credible.

Next, we present some practical constraints in minimization of the total recycling expense.

The first type of constraints is on material flow balance of network. It reads

$$\sum_j B_{ijt} + \sum_k C_{ikt} = R_{it}, \quad \forall i \in I, \ t \in T, \tag{7}$$

$$\sum_i B_{ijt} = \sum_k D_{jkt}, \quad \forall j \in J, \ t \in T, \tag{8}$$

$$\sum_l E_{klt} = \alpha \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K, \ t \in T, \tag{9}$$

$$\sum_s Q1_{kst} = \beta_1 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K, \ t \in T, \tag{10}$$

$$\sum_s Q2_{kst} = \beta_2 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K, \ t \in T, \tag{11}$$

$$\sum_p Q3_{kpt} = \beta_3 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K,\ t \in T, \tag{12}$$

$$\sum_q Q4_{kqt} = \beta_4 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K,\ t \in T, \tag{13}$$

$$\sum_r Q5_{krt} = \beta_5 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K,\ t \in T, \tag{14}$$

$$\sum_v Q6_{kvt} = \beta_6 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K,\ t \in T, \tag{15}$$

$$\sum_w Q7_{kwt} = \beta_7 \left(\sum_i C_{ikt} + \sum_j D_{jkt} \right), \quad \forall k \in K,\ t \in T, \tag{16}$$

$$\sum_u F_{lut} = \eta \sum_k E_{klt}, \quad \forall l \in L,\ t \in T, \tag{17}$$

$$\sum_m Q8_{lmt} = \eta_1 \sum_k E_{klt}, \quad \forall l \in L,\ t \in T, \tag{18}$$

$$\sum_u Q9_{lnt} = \eta_2 \sum_k E_{klt}, \quad \forall l \in L,\ t \in T. \tag{19}$$

The second type of constraints is on capacities of collection centers, dismantlers, shredders, and landfills. Owing to randomness of capacities, it says that the following stochastic inequalities should be satisfied:

$$\sum_i B_{ijt} \le \widehat{ca}_{jt}, \quad \forall j \in J,\ t \in T, \tag{20}$$

$$\sum_i C_{ikt} + \sum_j D_{jkt} \le \widehat{ca}_{kt} \cdot O_{kt}, \quad \forall k \in K,\ t \in T, \tag{21}$$

$$\sum_k E_{klt} \le \widehat{ca}_{lt} \cdot O_{lt}, \quad \forall l \in L,\ t \in T, \tag{22}$$

$$\sum_l F_{lut} \le \widehat{ca}_{ut}, \quad \forall u \in U,\ t \in T, \tag{23}$$

The third type of constraints is on the limited demands in secondary markets for the used components. Since the demands are random, the following stochastic inequalities hold:

$$\sum_k Q1_{kst} \le \widehat{de}_{1st}, \quad \forall s \in S,\ t \in T, \tag{24}$$

$$\sum_k Q2_{kst} \le \widehat{de}_{2st}, \quad \forall s \in S,\ t \in T. \tag{25}$$

The last type of constraints is on nonnegativity of decision variables and binary variables:

$$\begin{aligned} & B_{ijt}, C_{ikt}, D_{jkt}, E_{klt}, F_{lut}, Q1_{kst}, Q2_{kst}, Q3_{kpt}, Q4_{kqt}, Q5_{krt}, \\ & \quad Q6_{kvt}, Q7_{kwt}, Q8_{lmt}, Q9_{lnt} \ge 0, \\ & \qquad \forall i, j, k, l, s, m, n, p, q, r, v, w, u, t, \end{aligned} \tag{26}$$

$$O_{kt}, O_{lt} \in \{0, 1\}, \quad \forall k \in K,\ l \in L,\ t \in T. \tag{27}$$

Consequently, we obtain a polymorphic uncertain optimization model (PUOM) for the management problem of the ELV recovery system:

$$\begin{aligned} \min \quad & \widetilde{\pi} \\ \text{subject to} \quad & (7) - (27). \end{aligned} \tag{28}$$

Remark 2. Note that in (20)-(23), the capacities for the collection centers, dismantlers, shredders, secondary markets, and landfill are supposed to be random. This assumption is based on the given probability distribution inferred from statistical data of capacity, especially after long-term practical production. In [20], the capacity of sorting entities for recycling the ELVs was also assumed to be random.

Remark 3. Compared with the deterministic model built in [18], PUOM (28) takes into account the fuzziness of cost and selling price, as well as the randomness of capacity and demand. Instead of simply describing the unit cost and selling price by interval parameters as done in [22], we characterize them by fuzzy sets which can contain more uncertain information, especially those perceptual evaluations of decision-makers in practice. Consequently, the proposed PUOM (28) in this paper is a polymorphic uncertain programming problem.

Remark 4. Since any uncertain optimization problem has no any optimal solution from the viewpoint of standard optimization theory, we have to make an optimal decision by a compromising programming approach, as done in [24]. Specifically, chance-constrained and multiobjective optimization approach will be first proposed to transform the polymorphic uncertain optimization problem into a deterministic equivalent formulation in Section 3.1. Then, an interactive algorithm will be developed to find a compromising solution for the original uncertain optimization model on the basis of analytic tools and the existing powerful algorithms in the classical optimization theory.

3. Unified Compromising Programming Approach and an Interactive Algorithm

In this section, we intend to develop a unified compromising programming approach to treat the PUOM (28).

Our basic idea can be stated as follows. By chance-constrained programming approach, we first hedge randomness of constraints in PUOM (28) such that the obtained model is only involved with fuzzy parameters. Then, we construct an auxiliary multiple-objective optimization problem

(MOOP) to convert the fuzzy model into a mixed integer linear programming model. Finally, we develop an interactive algorithm to find the compromising solution of the MOOP.

3.1. Unified Compromising Programming Approach. For simplicity of statement, we now only consider a linear stochastic constraint

$$a^T x \leq \widehat{b}, \tag{29}$$

where $x \in R^e$ is a vector of decision variables, $a \in R^e$ is given crisp vector of coefficients, and $\widehat{b}$ is a random variable with probability distribution function $F_{\widehat{b}}(\cdot)$.

Based on the idea of chance-constrained programming approach, equivalent deterministic formulation of (29) can be obtained (see, for example, [22–24, 28, 29]). Specifically, for a given confidence level $1-\delta$ ($\delta \in [0,1]$), (29) is equivalent to that the following inequality:

$$Pr\left(a^T x \leq \widehat{b}\right) \geq 1-\delta \tag{30}$$

always holds for any $\delta \in [0,1]$, where $Pr(\cdot)$ represents the probability that a stochastic inequality holds. The constraint (30) can be replaced by

$$F_{\widehat{b}}\left(a^T x\right) \leq \delta. \tag{31}$$

Thus, by definition of probability distribution function, (31) can be approximated by an ordinary crisp constraint:

$$a^T x \leq F_{\widehat{b}}^{-1}(\delta) \tag{32}$$

for a given violation degree δ. Particularly, the random parameter $\widehat{b}$ is subject to normal distribution, i.e., $\widehat{b} \sim N(\mu_{\widehat{b}}, \sigma_{\widehat{b}}^2)$, where $\mu_{\widehat{b}}$ and $\sigma_{\widehat{b}}$ are the mean and standard deviation, respectively. Let $\Phi(\cdot)$ express the standard normal distribution function. Then, (32) reads

$$a^T x \leq \mu_{\widehat{b}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{b}}. \tag{33}$$

Let $F_{\widehat{ca}_{jt}}(\cdot)$, $F_{\widehat{ca}_{kt}}(\cdot)$, $F_{\widehat{ca}_{lt}}(\cdot)$, $F_{\widehat{ca}_{ut}}(\cdot)$, $F_{\widehat{de}_{1st}}(\cdot)$, and $F_{\widehat{de}_{2st}}(\cdot)$ be the probability distribution functions of the random variables $\widehat{ca}_{jt}$, $\widehat{ca}_{kt}$, $\widehat{ca}_{lt}$, $\widehat{ca}_{ut}$, $\widehat{de}_{1st}$, and $\widehat{de}_{2st}$, respectively. From (32), it follows that, for a given violation degree δ, the constraints (20)-(25) are replaced by

$$\sum_i B_{ijt} \leq F_{\widehat{ca}_{jt}}^{-1}(\delta), \quad \forall j \in J,\ t \in T, \tag{34}$$

$$\sum_i C_{ikt} + \sum_j D_{jkt} \leq F_{\widehat{ca}_{kt}}^{-1}(\delta) \cdot O_{kt}, \quad \forall k \in K,\ t \in T, \tag{35}$$

$$\sum_k E_{klt} \leq F_{\widehat{ca}_{lt}}^{-1}(\delta) \cdot O_{lt}, \quad \forall l \in L,\ t \in T, \tag{36}$$

$$\sum_l F_{lut} \leq F_{\widehat{ca}_{ut}}^{-1}(\delta), \quad \forall u \in U,\ t \in T, \tag{37}$$

$$\sum_k Q3_{kst} \leq F_{\widehat{de}_{1st}}^{-1}(\delta), \quad \forall s \in S,\ t \in T, \tag{38}$$

$$\sum_k Q4_{kst} \leq F_{\widehat{de}_{2st}}^{-1}(\delta), \quad \forall s \in S,\ t \in T. \tag{39}$$

If all the probability distributions are normal, then from (33), we know that (20)-(25) can be further rewritten as

$$\sum_i B_{ijt} \leq \mu_{\widehat{ca}_{jt}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{ca}_{jt}}, \quad \forall j \in J,\ t \in T, \tag{40}$$

$$\sum_i C_{ikt} + \sum_j D_{jkt} \leq \left(\mu_{\widehat{ca}_{kt}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{ca}_{kt}}\right) \cdot O_{kt}, \quad \forall k \in K,\ t \in T, \tag{41}$$

$$\sum_k E_{klt} \leq \left(\mu_{\widehat{ca}_{lt}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{ca}_{lt}}\right) \cdot O_{lt}, \quad \forall l \in L,\ t \in T, \tag{42}$$

$$\sum_l F_{lut} \leq \mu_{\widehat{ca}_{ut}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{ca}_{ut}}, \quad \forall u \in U,\ t \in T, \tag{43}$$

$$\sum_k Q3_{kst} \leq \mu_{\widehat{de}_{1st}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{de}_{1st}}, \quad \forall s \in S,\ t \in T, \tag{44}$$

$$\sum_k Q4_{kst} \leq \mu_{\widehat{de}_{2st}} + \Phi^{-1}(\delta) \cdot \sigma_{\widehat{de}_{2st}}, \quad \forall s \in S,\ t \in T. \tag{45}$$

We are now in a position to treat the fuzzy objective function in PUOM (28).

Since it is assumed that all the fuzzy parameters in $\widetilde{\pi}$ are subject to trapezoidal membership functions, $\widetilde{\pi}$ is a trapezoidal fuzzy set as a sum of trapezoidal fuzzy ones (see [25, 30, 31]). Denote $\widetilde{\pi} = (\pi^p, \pi^{m_1}, \pi^{m_2}, \pi^o)$. Instead of minimizing $(\pi^p + \pi^{m_1} + \pi^{m_2} + \pi^o)/4$ as in [19, 32, 33], we replace minimization of a fuzzy objective $\widetilde{\pi}$ by minimizing an integrated crisp objective function, defined by the membership functions of fuzzified $\pi^{m_1} + \pi^{m_2}$), $(\pi^o - \pi^{m_2})$, and $(\pi^{m_1} - \pi^p)$ (see model (57). To minimize the total cost and capture the uncertain (fuzzy) information in the total cost function, we first need to construct an auxiliary multiobjective optimization problem as follows:

$$\begin{aligned} \min \quad & Z_1 = \pi^{m_1} + \pi^{m_2} \\ \max \quad & Z_2 = \pi^{m_1} - \pi^p \\ \min \quad & Z_3 = \pi^o - \pi^{m_2} \\ \text{s.t.} \quad & (7)-(19), (26)-(27), (34)-(39), \end{aligned} \tag{46}$$

where

$$Z_1 = \sum_k \sum_t \left(f_{kt}^{m_1} + f_{kt}^{m_2}\right) O_{kt} + \sum_l \sum_t \left(f_{lt}^{m_1} + f_{lt}^{m_2}\right) O_{lt} + \sum_i \sum_j \sum_t \left(tc_{ijt}^{m_1}\right.$$

$$+ tc_{ijt}^{m_2}\Big) B_{ijt} d_{ij} + \sum_i \sum_k \sum_t \left(tc_{ikt}^{m_1} + tc_{ikt}^{m_2}\right) C_{ikt} d_{ik}$$
$$+ \sum_j \sum_k \sum_t \Big(tc_{jkt}^{m_1}$$
$$+ tc_{jkt}^{m_2}\Big) D_{jkt} d_{jk} + \sum_k \sum_l \sum_t \left(tc_{klt}^{m_1} + tc_{klt}^{m_2}\right) E_{klt} d_{kl}$$
$$+ \sum_l \sum_u \sum_t \left(tc_{lut}^{m_1}\right.$$
$$\left.+ tc_{lut}^{m_2}\right) F_{lut} d_{lu} + \sum_i \sum_k \sum_t \left(pc_{kt}^{m_1} + pc_{kt}^{m_2}\right) C_{ikt}$$
$$+ \sum_j \sum_k \sum_t \left(pc_{kt}^{m_1}\right.$$
$$\left.+ pc_{kt}^{m_2}\right) D_{jkt} + \sum_k \sum_l \sum_t \left(pc_{st}^{m_1} + pc_{st}^{m_2}\right) E_{klt}$$
$$+ \sum_l \sum_u \sum_t \left(pc_{ut}^{m_1}\right.$$
$$\left.+ pc_{ut}^{m_2}\right) F_{lut}$$
$$+ \sum_k \sum_s \sum_t \left(\left(tc_{kst}^{m_1} + tc_{kst}^{m_2}\right) d_{ks}\right.$$
$$\left.- \left(s_{1t}^{m_1} + s_{1t}^{m_2}\right)\right) Q1_{kst}$$
$$+ \sum_k \sum_s \sum_t \left(\left(tc_{kst}^{m_1} + tc_{kst}^{m_2}\right) d_{ks}\right.$$
$$\left.- \left(s_{2t}^{m_1} + s_{2t}^{m_2}\right)\right) Q2_{kst}$$
$$+ \sum_k \sum_p \sum_t \left(\left(tc_{kpt}^{m_1} + tc_{kpt}^{m_2}\right) d_{kp}\right.$$
$$\left.- \left(s_{3t}^{m_1} + s_{3t}^{m_2}\right)\right) Q3_{kpt}$$
$$+ \sum_k \sum_q \sum_t \left(\left(tc_{kqt}^{m_1} + tc_{kqt}^{m_2}\right) d_{kq}\right.$$
$$\left.- \left(s_{4t}^{m_1} + s_{4t}^{m_2}\right)\right) Q4_{kqt}$$
$$+ \sum_k \sum_r \sum_t \left(\left(tc_{krt}^{m_1} + tc_{krt}^{m_2}\right) d_{kr}\right.$$
$$\left.- \left(s_{5t}^{m_1} + s_{5t}^{m_2}\right)\right) Q5_{krt}$$
$$+ \sum_k \sum_v \sum_t \left(\left(tc_{kvt}^{m_1} + tc_{kvt}^{m_2}\right) d_{kv}\right.$$
$$\left.- \left(s_{6t}^{m_1} + s_{6t}^{m_2}\right)\right) Q6_{kvt}$$
$$+ \sum_k \sum_w \sum_t \left(\left(tc_{kwt}^{m_1}\right.\right.$$
$$\left.\left.+ tc_{kwt}^{m_2}\right) d_{kw} - \left(s_{7t}^{m_1} + s_{7t}^{m_2}\right)\right) Q7_{kwt}$$
$$+ \sum_l \sum_m \sum_t \left(\left(tc_{lmt}^{m_1} + tc_{lmt}^{m_2}\right) d_{lm}\right.$$
$$\left.- \left(z_{1t}^{m_1} + z_{1t}^{m_2}\right)\right) Q8_{lmt}$$
$$+ \sum_l \sum_n \sum_t \left(\left(tc_{lnt}^{m_1} + tc_{lnt}^{m_2}\right) d_{ln}\right.$$
$$\left.- \left(z_{2t}^{m_1} + z_{2t}^{m_2}\right)\right) Q9_{lnt}, \tag{47}$$

$$Z_2 = \sum_k \sum_t \left(f_{kt}^{m_1} - f_{kt}^{p}\right) O_{kt} + \sum_l \sum_t \left(f_{lt}^{m_1} - f_{lt}^{p}\right) O_{lt}$$
$$+ \sum_i \sum_j \sum_t \Big(tc_{ijt}^{m_1}$$
$$- tc_{ijt}^{p}\Big) B_{ijt} d_{ij} + \sum_i \sum_k \sum_t \left(tc_{ikt}^{m_1} - tc_{ikt}^{p}\right) C_{ikt} d_{ik}$$
$$+ \sum_j \sum_k \sum_t \Big(tc_{jkt}^{m_1}$$
$$- tc_{jkt}^{p}\Big) D_{jkt} d_{jk} + \sum_k \sum_l \sum_t \left(tc_{klt}^{m_1} - tc_{klt}^{p}\right) E_{klt} d_{kl}$$
$$+ \sum_l \sum_u \sum_t \Big(tc_{lut}^{m_1}$$
$$- tc_{lut}^{p}\Big) F_{lut} d_{lu} + \sum_i \sum_k \sum_t \left(pc_{kt}^{m_1} - pc_{kt}^{p}\right) C_{ikt}$$
$$+ \sum_j \sum_k \sum_t \Big(pc_{kt}^{m_1}$$
$$- pc_{kt}^{p}\Big) D_{jkt} + \sum_k \sum_l \sum_t \left(pc_{st}^{m_1} - pc_{st}^{p}\right) E_{klt}$$
$$+ \sum_l \sum_u \sum_t \Big(pc_{ut}^{m_1}$$
$$- pc_{ut}^{p}\Big) F_{lut}$$
$$+ \sum_k \sum_s \sum_t \left(\left(tc_{kst}^{m_1} - tc_{kst}^{p}\right) d_{ks}\right.$$
$$\left.- \left(s_{1t}^{m_1} - s_{1t}^{p}\right)\right) Q1_{kst}$$
$$+ \sum_k \sum_s \sum_t \left(\left(tc_{kst}^{m_1} - tc_{kst}^{p}\right) d_{ks} - \left(s_{2t}^{m_1} - s_{2t}^{p}\right)\right) Q2_{kst}\Big)$$
$$+ \sum_k \sum_p \sum_t \left(\left(tc_{kpt}^{m_1} - tc_{kpt}^{p}\right) d_{kp}\right.$$
$$\left.- \left(s_{3t}^{m_1} - s_{3t}^{p}\right)\right) Q3_{kpt}$$
$$+ \sum_k \sum_q \sum_t \left(\left(tc_{kqt}^{m_1} - tc_{kst}^{p}\right) d_{kq}\right.$$
$$\left.- \left(s_{4t}^{m_1} - s_{4t}^{p}\right)\right) Q4_{kqt}$$
$$+ \sum_k \sum_r \sum_t \left(\left(tc_{krt}^{m_1} - tc_{krt}^{p}\right) d_{kr}\right.$$
$$\left.- \left(s_{5t}^{m_1} - s_{5t}^{p}\right)\right) Q5_{krt}$$

$$+\sum_k\sum_v\sum_t\left(\left(tc_{kvt}^{m_1}-tc_{kvt}^{p}\right)d_{kv}-\left(s_{6t}^{m_1}-s_{6t}^{p}\right)\right)Q6_{kvt}$$
$$+\sum_k\sum_w\sum_t\left(\left(tc_{kwt}^{m_1}-tc_{kwt}^{p}\right)d_{kw}-\left(s_{7t}^{m_1}-s_{7t}^{p}\right)\right)Q7_{kwt}$$
$$+\sum_l\sum_m\sum_t\left(\left(tc_{lmt}^{m_1}-tc_{lmt}^{p}\right)d_{lm}-\left(z_{1t}^{m_1}-z_{1t}^{p}\right)\right)Q8_{lmt}$$
$$+\sum_l\sum_n\sum_t\left(\left(tc_{lnt}^{m_1}-tc_{lnt}^{p}\right)d_{ln}-\left(z_{2t}^{m_1}-z_{2t}^{p}\right)\right)Q9_{lnt} \quad (48)$$

and

$$Z_3=\sum_k\sum_t\left(f_{kt}^{o}-f_{kt}^{m_2}\right)O_{kt}+\sum_l\sum_t\left(f_{lt}^{o}-f_{lt}^{m_2}\right)O_{lt}$$
$$+\sum_i\sum_j\sum_t\left(tc_{ijt}^{o}-tc_{ijt}^{m_2}\right)B_{ijt}d_{ij}$$
$$+\sum_i\sum_k\sum_t\left(tc_{ikt}^{o}-tc_{ikt}^{m_2}\right)C_{ikt}d_{ik}$$
$$+\sum_j\sum_k\sum_t\left(tc_{jkt}^{o}-tc_{jkt}^{m_2}\right)D_{jkt}d_{jk}$$
$$+\sum_k\sum_l\sum_t\left(tc_{klt}^{o}-tc_{klt}^{m_2}\right)E_{klt}d_{kl}$$
$$+\sum_l\sum_u\sum_t\left(tc_{lut}^{o}-tc_{lut}^{m_2}\right)F_{lut}d_{lu}$$
$$+\sum_i\sum_k\sum_t\left(pc_{kt}^{o}-pc_{kt}^{m_2}\right)C_{ikt}$$
$$+\sum_j\sum_k\sum_t\left(pc_{kt}^{o}-pc_{kt}^{m_2}\right)D_{jkt}$$
$$+\sum_k\sum_l\sum_t\left(pc_{st}^{o}-pc_{st}^{m_2}\right)E_{klt}$$
$$+\sum_l\sum_u\sum_t\left(pc_{ut}^{o}-pc_{ut}^{m_2}\right)F_{lut}$$
$$+\sum_k\sum_s\sum_t\left(\left(tc_{kst}^{o}-tc_{kst}^{m_2}\right)d_{ks}-\left(s_{1t}^{o}-s_{1t}^{m_2}\right)\right)Q1_{kst}$$
$$+\sum_k\sum_s\sum_t\left(\left(tc_{kst}^{o}-tc_{kst}^{m_2}\right)d_{ks}-\left(s_{2t}^{o}-s_{2t}^{m_2}\right)\right)Q2_{kst}$$
$$+\sum_k\sum_p\sum_t\left(\left(tc_{kpt}^{o}-tc_{kpt}^{m_2}\right)d_{kp}-\left(s_{3t}^{o}-s_{3t}^{m_2}\right)\right)\cdot Q3_{kpt}$$
$$+\sum_k\sum_q\sum_t\left(\left(tc_{kqt}^{o}-tc_{kqt}^{m_2}\right)d_{kq}-\left(s_{4t}^{o}-s_{4t}^{m_2}\right)\right)Q4_{kqt}$$
$$+\sum_k\sum_r\sum_t\left(\left(tc_{krt}^{o}-tc_{krt}^{m_2}\right)d_{kr}-\left(s_{5t}^{o}-s_{5t}^{m_2}\right)\right)Q5_{krt}$$
$$+\sum_k\sum_v\sum_t\left(\left(tc_{kvt}^{o}-tc_{kvt}^{m_2}\right)d_{kv}-\left(s_{6t}^{o}-s_{6t}^{m_2}\right)\right)Q6_{kvt}$$
$$+\sum_k\sum_w\sum_t\left(\left(tc_{kwt}^{o}-tc_{kwt}^{m_2}\right)d_{kw}-\left(s_{7t}^{o}-s_{7t}^{m_2}\right)\right)\cdot Q7_{kwt}$$
$$+\sum_l\sum_m\sum_t\left(\left(tc_{lmt}^{o}-tc_{lmt}^{m_2}\right)d_{lm}-\left(z_{1t}^{o}-z_{1t}^{m_2}\right)\right)Q8_{lmt}$$
$$+\sum_l\sum_n\sum_t\left(\left(tc_{lnt}^{o}-tc_{lnt}^{m_2}\right)d_{ln}-\left(z_{2t}^{o}-z_{2t}^{m_2}\right)\right)Q9_{lnt}. \quad (49)$$

Clearly, the first objective in (46) is to minimize the total cost and the last two objectives are used to capture the uncertain information in the total cost as much as possible. In addition, if (34)-(39) in model (46) are replaced by (40)-(45), then we get a special case of model (46) under assumption of normal distribution.

Remark 5. With the proposed unified compromising programming approach, the randomness of constraints in PUOM (28) first vanishes by chance-constrained programming method. It is possible that the feasible region of PUOM (28) is empty if the choice of violation degree δ is very small [24]. In other words, a suitable choice of violation degree is important to the unified compromising programming approach, which will be further addressed in Section 4. It is also noted that the constraint of PUOM (28) is involved with the inverse of distribution function. So, there does not exist an explicit expression of such a constraint in the case that it is difficult to calculate the inverse of distribution function. Consequently, many powerful algorithms in standard optimization theory can not be applied to solve PUOM (28). Under assumption of normal distribution, explicit expressions of the constraints can be obtained (see the case study in Section 4).

Remark 6. Similar to [25, 31], we construct an auxiliary multiobjective optimization model (46) to hedge the fuzziness of the objective function in (28). Intuitively, the reason why we transform a fuzzy objective function into a three-objective one is that it can push the trapezoidal possibility distribution of the fuzzy total cost to the left as far as possible (see Figure 3).

Actually, the first objective in (46) implies the total cost, especially the part with degree of membership 1, is to be minimized by minimizing the center value. The third objective in (46) can minimize the area of the region (II) in Figure 3 so as to reduce the risk of higher cost, while the second objective in (46) can maximize the area of region (I) in Figure 3 so as to increase the possibility of obtaining lower cost. Clearly, the crisp model (46) is a deterministic

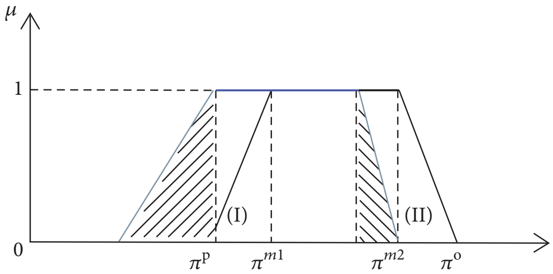


Figure 3: Principle of three-objective optimization approach.

equivalent formulation of the PUOM (28). To the best of our knowledge, it is the first time that the management problem of ELV recovery is treated by this approach in a polymorphic uncertain environment. For example, an expectation method was recently presented to convert the fuzzy model into a crisp one in [19].

3.2. Interactive Algorithm. With the preparation in Section 3.1, we now develop an interactive algorithm to find a compromising solution of PUOM (28), different from the hybrid heuristic algorithm developed in [24].

Algorithm 1.

Step 1. Choose an acceptable violation degree δ for the random constraints. Solve the following three mixed integer linear programming problems (MILP):

$$\begin{aligned} \min \quad & Z_1 \\ \text{s.t.} \quad & (7)-(19), (26)-(27), (34)-(39), \end{aligned} \tag{50}$$

$$\begin{aligned} \max \quad & Z_2 \\ \text{s.t.} \quad & (7)-(19), (26)-(27), (34)-(39), \end{aligned} \tag{51}$$

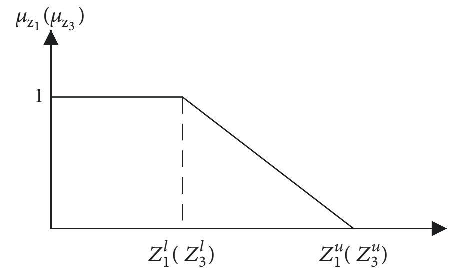
$$\begin{aligned} \min \quad & Z_3 \\ \text{s.t.} \quad & (7)-(19), (26)-(27), (34)-(39). \end{aligned} \tag{52}$$

Denote x^{1*}, x^{2*}, and x^{3*} by the optimal solutions of (50), (51), and (52), respectively. The corresponding optimal values of the three objective functions are referred to as Z_1^l, Z_2^u, and Z_3^l, respectively. Compute

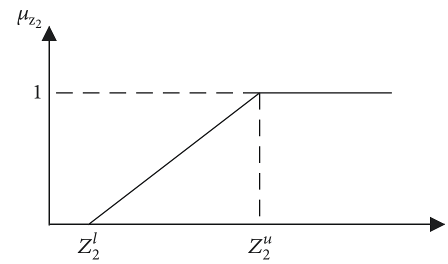
$$\begin{aligned} Z_1^u &= \max\left\{Z_1\left(x^{2*}\right), Z_1\left(x^{3*}\right)\right\}, \\ Z_2^l &= \min\left\{Z_2\left(x^{1*}\right), Z_2\left(x^{3*}\right)\right\}, \\ Z_3^u &= \max\left\{Z_3\left(x^{1*}\right), Z_3\left(x^{2*}\right)\right\}. \end{aligned} \tag{53}$$

Clearly, Z_i^l and Z_i^u are the upper and lower bounds of the i-th objective function, $i = 1, 2, 3$.

Step 2. With Z_i^l and Z_i^u, formulate a trapezoidal membership function for the objective function Z_i. Specifically, we fuzzify



(a) Membership function for $Z_1(Z_3)$



(b) Membership function for Z_2

Figure 4: Fuzzification of the three objective functions.

Z_1 and Z_2 and Z_3 by specifying their membership functions (also see Figures 4(a) and 4(b)):

$$\mu_{\widetilde{Z}_1}\left(Z_1\right) = \begin{cases} 1, & Z_1 \le Z_1^l \\ \dfrac{Z_1^u - Z_1}{Z_1^u - Z_1^l}, & Z_1^l \le Z_1 \le Z_1^u \\ 0, & Z_1 \ge Z_1^u, \end{cases} \tag{54}$$

$$\mu_{\widetilde{Z}_2}\left(Z_2\right) = \begin{cases} 0, & Z_2 \le Z_2^l \\ \dfrac{Z_2 - Z_2^l}{Z_2^u - Z_2^l}, & Z_2^l \le Z_2 \le Z_2^u \\ 1, & Z_2 \ge Z_2^u, \end{cases} \tag{55}$$

and

$$\mu_{\widetilde{Z}_2}\left(Z_3\right) = \begin{cases} 1, & Z_3 \le Z_3^l \\ \dfrac{Z_3^u - Z_3}{Z_3^u - Z_3^l}, & Z_3^l \le Z_3 \le Z_3^u \\ 0, & Z_3 \ge Z_3^u, \end{cases} \tag{56}$$

respectively.

Step 3. The decision-maker decides a compensation coefficient γ and a weight θ_h for the h-th objective function, $h = 1, 2, 3$. Then, an integrated model is defined by

$$\begin{aligned} \max \quad & \lambda(x) = \gamma\lambda_0 + (1-\gamma)\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x) \\ \text{s.t.} \quad & \lambda_0 \le \mu_{\widetilde{Z}_h}(x), \quad h = 1, 2, 3, \\ & (7)-(19), (26)-(27), (34)-(39), \end{aligned} \tag{57}$$

where λ_0 is an auxiliary variable.

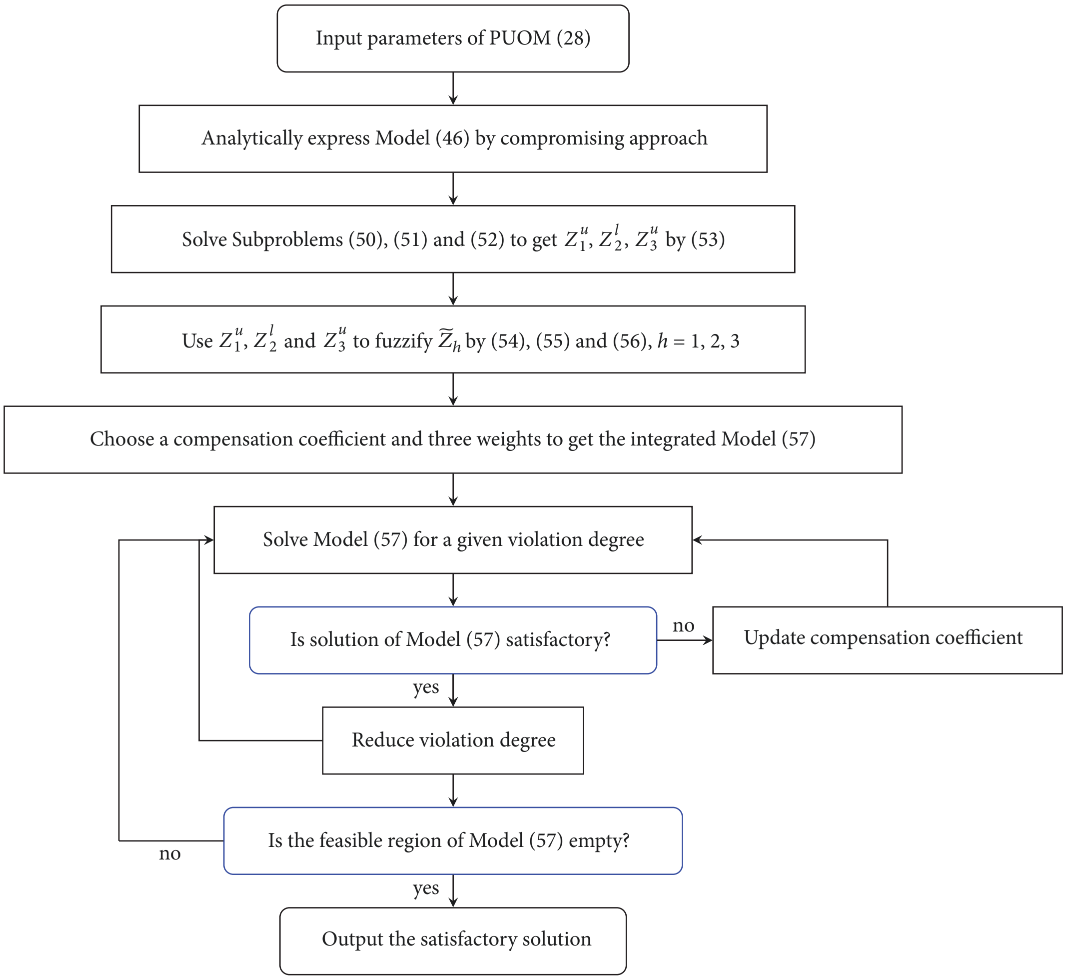


Figure 5: Logic chat of Algorithm 1.

Step 4. Select a violation degree δ^* as small as possible to ensure solution existence of the deterministic model (57).

Step 5. Solve model (57). Denote x^* and λ_0^* the optimal solution of (57). Clearly, corresponding to δ^*, the satisfaction degree of the three objective functions at least attains λ_0^*.

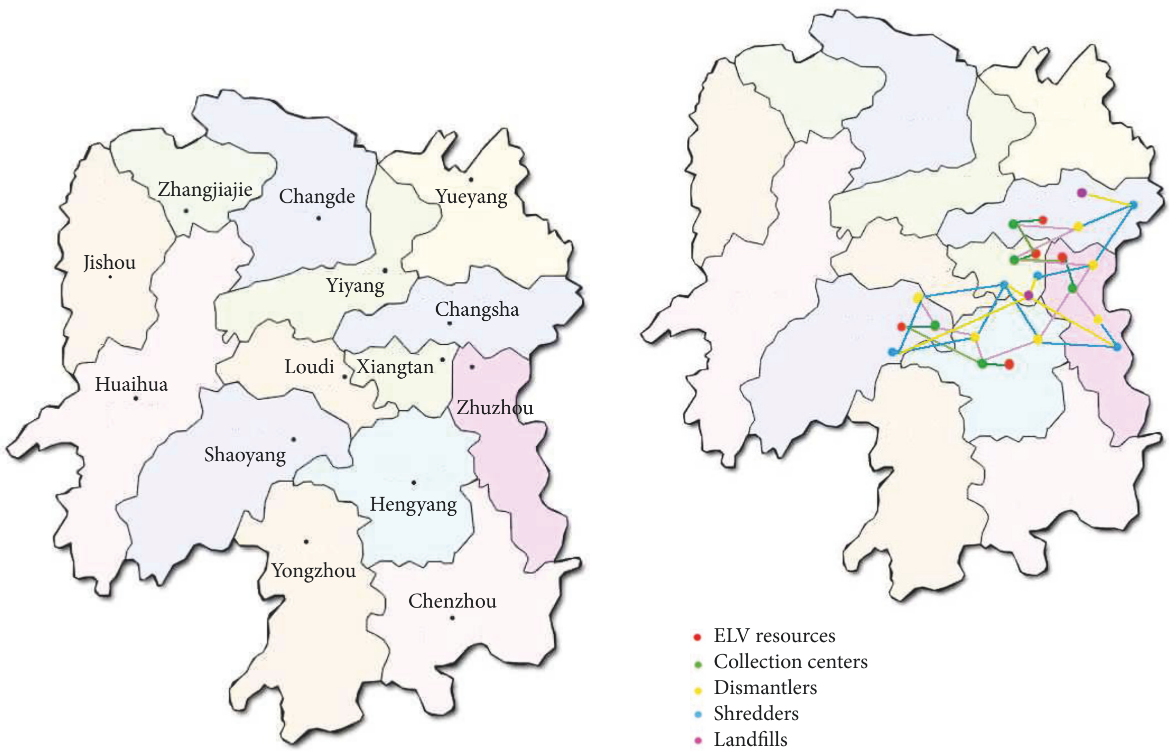
Step 6. If the decision-maker is satisfied with this current compromising solution, go to Step 7. Otherwise, update the value of compensation coefficient by $\gamma =: \gamma + \Delta\gamma$, where $1 - \gamma > \Delta\gamma > 0$. Return to Step 5.

Step 7. Choose a smaller δ^*. If the feasible region of (57) is empty for δ^*, then the algorithm stops and the decision-maker determines the most satisfactory δ^*, x^* and λ_0^* amongst all of the previous numerical results. Otherwise, return to Step 5.

The logic of Algorithm 1 can be demonstrated by the flowchart in Figure 5.

Remark 7. In Step 2, the three membership functions defined by (54), (55), and (56) are degenerate trapezoidal functions. Since our aim is to minimize Z_1, smaller values of Z_1 than Z_1^l are always preferable. Thus, it is nature to make the degree of membership equal to 1 for any value of Z_1 less than Z_1^l. In this case, the left side of the membership function $\mu_{\widetilde{Z}_1}(Z_1)$ is degenerate. The similar reason can be used to explain the definitions of $\mu_{\widetilde{Z}_2}(Z_2)$ and $\mu_{\widetilde{Z}_3}(Z_3)$.

Remark 8. In Step 3, as done in [34], a fuzzy programming approach is employed to convert a multiobjective optimization problem into a single-objective problem such that an interactive algorithm is developed to find a compromising solution of the PUOM (28). Clearly, by maximizing the integrated degree of membership λ in model (57), we obtain a compromising solution such that both the total cost and its variance (the decision-making risk) become as smaller as possible. Actually, the first term in the objective function of model (57) describes the lower bound of the membership degree of all the three fuzzy objectives; greater lower bound means higher degree of overall satisfaction, with which the three objectives are simultaneously improved. The second term in the objective function of model (57) makes a trade-off between the overall satisfaction and the individual one.



(a) The map of Hunan province

(b) Recovery network of five key cities

Figure 6: Recovery network in Hunan province.

Remark 9. In [34], an interactive algorithm was developed to solve a problem of purchasing, production, and distribution, which is involved in multiple suppliers, one manufacturer, and multiple distribution centers. It is shown that this algorithm always generates unbalanced and balanced solutions based on the decision-maker's preferences. Similar to [34], we develop Algorithm 1 to find a compromising solution of the polymorphic uncertain recycling problems of ELVs in this paper. Numerical experiments in Sections 4 and 5 will show that Algorithm 1 can reveal more valuable managerial insights from the proposed model (2) than the solution methods available in the literature. Especially, by our algorithm, we can show how to choose an optimal compensation coefficient and a violation degree (see Section 4).

4. Case Study with Different Algorithmic Parameters

In this section, we will apply the presented model and algorithm in Sections 2 and 3 to solve practical ELV recovery management problems in Hunan, China.

4.1. Case Description. According to [3], China has built a number of ELV recycling enterprises. In this case study, we attempt to deal with the end-of-life car recovery management problem of the five key cities (Changsha, Zhuzhou, Xiangtan, Hengyang, and Shaoyang) in Hunan (see Figure 6), considering that the data can be collected completely.

For convenience, the centers of the five cities are regarded as the ELV sources, and all of the relevant collecting enters, dismantlers, shredders, landfills, secondary markets, and recycling factories are distributed in these cities with given locations (see Figure 6(b) and Tables 1–6). It is noted that, for some cities, there are more than one dismantler, secondary market, oil, or glass factory, or there is no any landfill, secondary market, rubber, or plastics factory in practice.

A part of available data on unit costs of transportation and processing, selling price and material weight percentages of ELVs are deregistered from [6] (see Tables 7–11). For simplifying this case study, we only consider a single-period recycling problem. Referring to the government data on scrapped vehicles [12], the amount of ELVs from the five sources are estimated by

$$\begin{aligned} R_1 &= 1073, \\ R_2 &= 587, \\ R_3 &= 418, \\ R_4 &= 1087, \\ R_5 &= 1077. \end{aligned} \tag{58}$$

The aim of this case study is to answer the following questions:

(1) How to determine an optimal transportation plan for the ELV recycling network?

Table 1: Size of the decision variables.

I	J	K	L	U	S	P	Q	R	V	W	M	N
5	5	6	5	2	2	2	2	2	2	2	2	2

Table 2: Sites of all items.

	Changsha	Zhuzhou	Xiangtan	Hengyang	Shaoyang
Resource	1	2	3	4	5
Collection center	1	2	3	4	5
Dismantler	1	2,3	4	6	5
Shredder	2	1	3	5	4
Landfill	2	-	1	-	-
Secondary market	1,2	-	-	-	-
Steel mill	1,2	-	-	-	-
Non-ferrous smeltery	1	-	-	2	-
Oil factory	1,2	-	-	-	-
Battery factory	1	-	-	2	-
Rubber factory	-	1	-	-	2
Glass factory	1,2	-	-	-	-
Plastics factory	-	-	1	-	2

Table 3: Distance between areas (km).

	Resources					Collection centers				
	1	2	3	4	5	1	2	3	4	5
Dismantlers										
1	12.8	39.7	40	150.1	186.1	21.8	59.8	46.4	150.9	153.1
2	56.9	11.1	23.7	114.1	178.4	60.2	13.8	36.3	116.4	138.7
3	46.3	5.7	18.5	120.3	177.6	49.8	22.9	31.9	122.2	139.2
4	126.3	82.9	82.4	44	148.4	124.9	64.8	81.8	48.8	105.1
5	157.3	146	134.1	90.1	28.2	148.8	143.3	121.6	84.3	15.5
6	149.6	118.9	111.5	22.5	93.4	144.2	107.3	103.6	16.6	53.3
Collection centers										
1	10	49.8	43.7	147.6	170.2	-	-	-	-	-
2	67.4	20.2	27.2	100.7	170.5	-	-	-	-	-
3	46.9	26.9	13.4	104.8	146.8	-	-	-	-	-
4	152	117	111.4	6.1	109.9	-	-	-	-	-
5	148.3	133.6	122.1	75.5	43.5	-	-	-	-	-

(2) What are the impacts of violation degree δ on the three objectives Z_1, Z_2, and Z_3 for a fixed compensation coefficient γ?

(3) What are the influences of compensation coefficient γ on the least satisfaction degree λ_0?

4.2. Numerical Solution of the ELV Recycling Model. We choose the weights of the three objectives $\theta_1 = 0.4$, $\theta_2 = 0.3$, and $\theta_3 = 0.3$, respectively. Then, we solve model (57) by Algorithm 1. The optimal values of the decision variables are reported in Table 12 in the case that $\delta = 0.1$ and $\gamma = 0.5$.

Table 12 indicates the follow-ing:

(1) All the ELVs from the five sources are transported to collection centers 1, 2, 4, and 5, while the quantities of transportation between the ELV sources and collection centers 3 and 6 are zeros.

(2) The most admissive quantity of ELVs from the ELV sources is 1935, which is actualized by the first collection center. The minimal quantity of transportation occurred to the second collection center (229 units of ELV).

(3) From the optimal results, all the 4242 ELVs are transported to the collection centers from the ELV sources. That is to say, there is no direct transportation between the ELV sources and the dismantlers.

(4) All the ELVs at collection centers 1, 2, 4, and 5 are transported to Dismantlers 1, 5, and 6.

(5) All the hulks are transported from the dismantlers to Shredders 2, 3, and 5. Then, from the shredders, the total 2630 tons of ferrous material and 169.68 tons of nonferrous material are sold to the steel mills and the nonferrous smelteries, respectively.

(6) The total disposal quantity is 637.3 tons and all the ASR are disposed in the two landfills.

Table 4: Continued Table 3.

	Shredders					Secondary markets	
	1	2	3	4	5	1	2
Dismantlers							
1	123.2	25.1	39.1	194.6	42.0	10.2	2.3
2	75.3	50.7	33.4	182.8	21.9	39.5	46.7
3	85.8	42.6	27.2	183.0	17.8	28.8	36.1
4	40.4	129.2	87.1	145.2	80.1	111.6	119.8
5	160.2	185.1	128.4	31.7	134.1	155.2	160.8
6	100.7	165.6	110.9	87.1	110.3	140.1	147.7
Landfills							
1	148.7	39.4	59.5	204.0	65.3	-	-
2	88.1	50.9	14.4	170.2	4.7	-	-
Steel mills							
1	117.8	33.0	29.7	185.1	33.8	-	-
2	114.7	33.3	27.2	184.0	30.8	-	-
Non-ferrous smelteries							
1	149.4	33.0	65.3	214.1	69.3	-	-
2	75.7	156.5	106.2	113.9	102.7	-	-

Table 5: Continued Table 4.

	Oil		Battery		Rubber		Glass		Plastics	
	1	2	1	2	1	2	1	2	1	2
Dismantlers										
1	12.8	8.7	6.6	177.7	36.1	200.6	7.6	5.5	43.3	164.6
2	53.4	53.8	42.7	143.54	17.3	191.5	40.6	51.3	29.0	144.2
3	42.8	43.6	32.1	149.3	9.8	191.2	30.1	41.0	24.5	146.3
4	121.9	129.2	115.2	72.9	85.6	157.5	115.3	126.2	81.0	98.2
5	153.6	171.4	157.5	86.9	142.9	39.9	161.9	168.5	128.1	31.5
6	145.1	158.6	143.4	30.7	118.5	100.2	145.7	155.4	107.1	39.8

Table 6: Probability distribution of capacity/demand (ton).

$\widehat{ca}_j$	$\widehat{ca}_k$	$\widehat{ca}_l$	$\widehat{ca}_u$	$\widehat{de}_{1s}$	$\widehat{de}_{2s}$
$N(2000, 50^2)$	$N(2000, 50^2)$	$N(1500, 45^2)$	$N(500, 20^2)$	$N(200, 10^2)$	$N(100, 5^2)$

Table 7: The fixed opening cost ($\times 10^6$ yuan).

$\widetilde{f}_k$	$\widetilde{f}_l$
(1.235,1.245,1.255,1.26)	(4.975,4.99,5.01,5.02)

Table 8: Unit processing cost (yuan/ton).

$\widetilde{pc}_k$	$\widetilde{pc}_l$	$\widetilde{pc}_u$
(1820,1920,2000,2080)	(240,260,280,300)	(440,480,520,550)

4.3. Impacts of Violation Degree. It is easy to see that the feasible region of model (57) is closely related to the violation degree δ. For a smaller violation degree, the feasible region becomes smaller because a decreasing δ implies higher restriction on capacities or demands. Thus, it is useful to analyze the impacts of violation degree on the optimal solution for the presented unified compromising optimization approach in this paper. For this, we change the violation degree δ with a step length of 0.01.

In Table 13, numerical results are given for different violation degrees with a fixed $\gamma = 0.5$.

Table 13 demonstrates the following:

(1) With an increasing violation degree, satisfactory degree of the solution by the proposed unified compromising optimization method becomes greater. On the other hand, from $\lambda_0 > 0.5$, it follows that the satisfaction degree of the compromising method can give a more satisfactory solution than the expectation method in the literature.

(2) Both of the center value and the lower deviation of the fuzzy objective function, Z_1 and Z_3, are increasing as the violation degree takes a smaller value, while the upper deviation Z_2 is decreasing.

(3) Since variations of the center value, the lower and upper deviations, seem to be greater within the same change of violation degree, it suggests that decision-makers should choose a violation degree as small as possible in practice,

Table 9: Unit transportation cost of each item (yuan/ton·km).

$\widetilde{tc}_{ij}$,$\widetilde{tc}_{ik}$	$\widetilde{tc}_{jk}$	$\widetilde{tc}_{kl}$	$\widetilde{tc}_{lu}$
(1.8,1.92,2.02,2.1)	(0.7,0.76,0.82,0.86)	(0.3,0.37,0.44,0.5)	(0.9,0.97,1.04,1.1)
$\widetilde{tc}_{ks}$	$\widetilde{tc}_{kp}$,$\widetilde{tc}_{lm}$,$\widetilde{tc}_{ln}$	$\widetilde{tc}_{kq}$	$\widetilde{tc}_{kr}$,$\widetilde{tc}_{kv}$,$\widetilde{tc}_{kw}$
(1.4,1.47,1.54,1.6)	(0.6,0.67,0.74,0.8)	(0.5,0.57,0.64,0.7)	(0.4,0.47,0.54,0.6)

Table 10: Unit selling price of each item type ($\times 10^3$yuan/ton).

$\widetilde{s}_{1t}$	$\widetilde{s}_{2t}$	$\widetilde{s}_{3t}$	$\widetilde{s}_{4t}$
(2.1,2.3,2.5,2.65)	(10.5,11.3,12.3,13)	(3.5,3.7,3.9,4.0)	(0.56,0.6,0.64,0.67)
$\widetilde{s}_{5t}$	$\widetilde{s}_{6t}$	$\widetilde{s}_{7t}$	$\widetilde{z}_{1t}$
(0.14,0.145,0.15,0.155)	(0.3,0.4,0.5,0.58)	(5,5.6,6.2,6.6)	(0.44,0.48,0.52,0.55)
$\widetilde{z}_{2t}$			
(1.4,1.47,1.54,1.6)			

Table 11: Weight percentage of each item.

α	β_1	β_2	β_3	β_4	β_5	β_6	β_7	η	η_1	η_2
0.81	0.06	0.04	0.017	0.013	0.03	0.015	0.015	15/81	62/81	4/81

Table 12: Numerical solution in the case that $\delta = 0.1$ and $\lambda = 0.5$.

Variable	Value	Variable	Value	Variable	Value	Variable	Value
$B_{1,4}$	1073	$E_{1,3}$	431.2	$Q2_{6,1}$	77.4	$Q6_{6,1}$	29.025
$B_{2,5}$	587	$E_{5,3}$	301.3	$Q3_{1,2}$	32.895	$Q7_{3,2}$	29.025
$B_{3,5}$	418	$E_{6,3}$	125	$Q3_{5,1}$	6.324	$Q7_{5,2}$	5.58
$B_{4,1}$	1087	$E_{6,5}$	144.23	$Q3_{6,1}$	32.895	$Q7_{2,1}$	29.025
$B_{5,1}$	848	$F_{2,1}$	210.3975	$Q4_{1,1}$	25.155	$Q8_{2,2}$	869.6
$B_{5,2}$	229	$F_{3,2}$	158.8043	$Q4_{5,1}$	4.836	$Q8_{3,2}$	656.4
$D_{1,6}$	1935	$F_{5,2}$	267.0982	$Q4_{6,2}$	25.155	$Q8_{5,2}$	1104
$D_{2,5}$	229	$Q1_{1,2}$	116.1	$Q5_{1,1}$	58.0	$Q9_{2,1}$	56.1065
$D_{4,1}$	930	$Q1_{5,1}$	22.32	$Q5_{5,2}$	11.16	$Q9_{3,1}$	42.3478
$D_{4,5}$	143	$Q1_{6,1}$	116.1	$Q5_{6,2}$	58.05	$Q9_{5,1}$	71.2262
$D_{5,1}$	1005	$Q2_{1,2}$	77.4	$Q6_{1,2}$	29.025		
$E_{1,2}$	1136.1	$Q2_{5,1}$	14.88	$Q6_{5,1}$	5.58		

Table 13: Optimal solutions of different violation degree ($\gamma = 0.5$).

δ	λ	λ_0	Z_1	Z_2	Z_3	∇Z_1	∇Z_2	∇Z_3
0.15	0.58486327	0.5061525	50622457.1	342850.6	269717.2	–	–	–
0.14	0.58485733	0.5061454	50622502.3	342849.1	269718.2	45.2	-1.5	1.0
0.13	0.58485261	0.5061407	50622650.9	342848.2	269718.9	14.9	-0.1	0.7
0.12	0.58484835	0.5061360	50622728.4	342847.2	269719.6	58.4	-1.0	0.7
0.11	0.58484195	0.5061289	50622844.6	342845.7	269720.6	106.2	-1.5	1.0
0.10	0.58483555	0.5061218	50622960.9	342844.2	269721.7	116.3	-1.5	1.1
0.09	0.58482881	0.5061139	50623026.2	342842.6	269722.8	65.3	-1.6	1.1
0.08	0.58482275	0.5061077	50623193.4	342841.3	269723.7	167.1	-1.3	0.9
0.07	0.58481635	0.5061006	50623309.9	342839.8	269724.8	116.5	-1.5	1.0
0.06	0.58480776	0.5060912	50623475.2	342837.8	269726.1	165.3	-2.0	1.4
0.05	0.58479702	0.5060794	50623681.1	342835.4	269727.8	205.9	-2.5	1.7
0.04	0.58478627	0.5060676	50623888.4	342832.9	269729.6	207.3	-2.5	1.7
0.03	0.58477089	0.5060503	50624126.1	342829.3	269732.1	237.7	-3.6	2.5
0.02	0.58475481	0.5060323	50624386.1	342825.5	269734.7	260.0	-3.8	2.6
0.01	0.58473918	0.5060109	50624154.1	342821.0	269737.8	-231.9	-4.5	3.1

Table 14: Impacts of different compensation coefficient ($\delta = 0.02$).

γ	λ	λ_0	Z_1	Z_2	Z_3
0.1	0.6477901	0.5051697	50571344.3	342645.3	269860.4
0.2	0.6319046	0.5056313	50605879.4	342741.7	269793.2
0.3	0.6162438	0.5060323	50624386.1	342825.5	269734.7
0.4	0.6004978	0.5059748	50618897.1	342813.5	269743.1
0.5	0.5847548	0.5060323	50624386.1	342825.5	269734.7
0.6	0.5690160	0.5060412	50624749.2	342827.4	269733.4
0.7	0.5532663	0.5060345	50624774.6	342826.0	269734.4
0.71	0.5516919	0.5060346	50624774.7	342826.1	269734.3
0.72	0.5502479	0.5156469	52976829.1	344834.1	268333.4
0.73	0.5490104	0.5156425	52976206.2	344833.2	268334.1
0.74	*0.5479271*	*0.5330710*	*57636118.5*	*348474.4*	*265793.9*
0.8	0.5444988	0.5330710	57636113.5	348474.3	265793.9
0.9	0.5387847	0.5330708	57636081.8	348474.3	265794.0

provided that the feasible region of model (57) is nonempty. In other words, one can obtain a better return with the same violation by this way.

4.4. Impacts of Compensation Coefficient. Since the compensation coefficient (γ) reflects importance of the least satisfaction degree in model (57), a suitable choice of compensation coefficient is necessary to any decision-maker. Actually, a higher value for γ implies that more attention is paid to a greater lower bound of satisfaction degree, corresponding to more balanced compromising solutions [25].

We are in a position to study how the compensation coefficient affects the satisfaction degree. For this, we solve model (57) by changing the value of compensation coefficient with a step length of 0.01. Additionally, from the results in Section 4.3, we fix $\delta = 0.02$. Numerical results are listed in Table 14.

From Table 14, it follows that

(1) With an increasing compensation coefficient, the value of λ_0 becomes greater, while the value of λ becomes smaller. When $\gamma > 0.71$, the least satisfaction degree λ_0, the center value Z_1, the upper deviations Z_2, and the lower deviations Z_3 all generate great changes.

(2) Both of the center value and the upper deviation of the fuzzy objective function, Z_1 and Z_2, are increasing as the compensation coefficient takes a greater value, while the lower deviation Z_3 is decreasing. This phenomenon implies that the membership degrees of the three objective functions not always become larger or smaller simultaneously.

(3) If the decision-maker prefers to a higher satisfaction degree λ_0, he/she could choose a relatively higher value of γ for an optimal solution. Table 14 shows that there exists a threshold value ($\gamma = 0.74$ or so for the given scenario).

5. Sensitivity Analysis of Model Parameters

In this section, by sensitivity analysis of model parameters, we attempt to reveal some valuable managerial implications from our model and algorithm. Specifically, we will address the following issues:

(1) How do the standard deviations (ST) of random coefficients and the variances of fuzzy coefficients affect the optimal strategy of the ELV recovery system?

(2) What are the impacts of the above deviations and variances on the satisfaction degree $\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x)$, the center value Z_1, and the deviations Z_2 and Z_3?

5.1. Impacts of Fuzzy Cost Coefficients. Since the cost coefficients in model (2) are fuzzy, we conduct sensitivity analysis by changing the variance of fuzzy sets so as to reveal what are their impacts on the optimal solution.

A change of cost coefficients often influences enterprise's decision. So, an interesting question is to answer whether there exist some differences among different types of cost coefficients or not.

We change the dispersion levels of different fuzzy cost coefficients in model (2) by a step length of 5% increment. An addition of 30 scenarios is conducted in order to obtain a generalization of the proposed model. The 30 scenarios are the combination of the 10 different levels of the fixed cost, 10 different levels of the transportation cost, and 10 different levels of the processing cost. Then, we implement Algorithm 1 to solve the corresponding models. Numerical results are presented in Tables 15, 16, and 17 and in Figure 7.

From Tables 15, 16, and 17 and Figure 7, it is clear that

(i) From Tables 15, 16, and 17, the increment in dispersion level of fixed and processing cost coefficients causes a change in choice of opening sites of dismantlers and shredders. But the increment in dispersion level of transportation cost coefficients only influences the choice of opening sites for the dismantlers. In any scenario, the number of opening points is not affected by the dispersion levels of fuzzy cost coefficients.

(ii) A larger dispersion level leads to a lower satisfaction degree $\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x)$. In Figure 7(a), it is seen that the processing cost has obvious influence on the satisfaction degree, compared with the fixed cost and the transportation cost in the range of 10%-25%.

Table 15: Impact of fixed cost coefficients' variance on choice of opening sites.

Open or not	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
K1	1	1	1	1	1	1	1	1	1	1
K2	0	0	0	0	0	0	0	0	0	0
K3	1	0	0	0	0	0	0	0	0	0
K4	0	1	1	0	0	0	1	0	0	1
K5	0	1	1	1	1	1	1	1	1	1
K6	1	0	0	1	1	1	0	1	1	0
L1	0	0	0	0	0	0	0	0	1	1
L2	1	1	1	1	1	1	1	1	1	1
L3	1	1	1	1	1	1	1	1	0	1
L4	0	0	0	0	0	0	0	0	0	0
L5	1	1	1	1	1	1	1	1	1	0

Table 16: Impact of processing cost coefficients' variance on choice of opening sites.

Open or not	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
k1	NA	1	1	1	1	0	0	1	1	1
k2	NA	1	0	0	0	1	1	1	1	0
k3	NA	1	0	1	0	1	0	0	0	0
k4	NA	0	1	0	1	1	1	1	0	0
k5	NA	0	1	0	0	0	0	0	0	1
k6	NA	0	0	1	1	0	1	0	1	1
L1	NA	0	0	1	0	1	1	0	0	0
L2	NA	1	0	0	0	0	0	1	1	1
L3	NA	1	1	1	1	1	1	1	1	1
L4	NA	0	1	0	1	0	0	0	0	0
L5	NA	1	1	1	1	1	1	1	1	1

Table 17: Impact of transportation cost coefficients' variance on choice of opening sites.

Open or not	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
K1	1	1	1	1	1	1	1	1	1	1
K2	0	1	0	0	1	0	0	1	1	0
K3	1	0	1	1	0	1	1	0	0	1
K4	1	1	1	1	1	1	1	0	0	0
K5	0	0	0	0	0	0	0	0	0	0
K6	0	0	0	0	0	0	0	1	1	1
L1	0	0	0	0	0	0	0	0	0	0
L2	1	1	1	1	1	1	1	1	1	1
L3	1	1	1	1	1	1	1	1	1	1
L4	0	0	0	0	0	0	0	0	0	0
L5	1	1	1	1	1	1	1	1	1	1

Beyond a threshold value (25% or so for the given scenario), their impacts on the satisfaction degree $\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x)$ have no sharp distinction.

(iii) From Figures 7(b), 7(c), and 7(d), the increment in cost dispersion level brings about the increase of the center value Z_1 and the deviations Z_2 and Z_3, no matter it is the fixed cost, the processing cost, or the transportation cost. The contribution from the processing costs is greater than those from the fixed cost and the transportation cost. Therefore, we suggest that it is the most important measure to improve the ELV recovery efficiency by adopting advanced processing technology and machinery equipment, which can raise the entire satisfaction degree and reduce the system cost.

5.2. Impacts of Fuzzy Selling Prices. Since the selling prices in model (2) are also fuzzy, we similarly conduct the sensitivity analysis of selling price by changing the variance of fuzzy

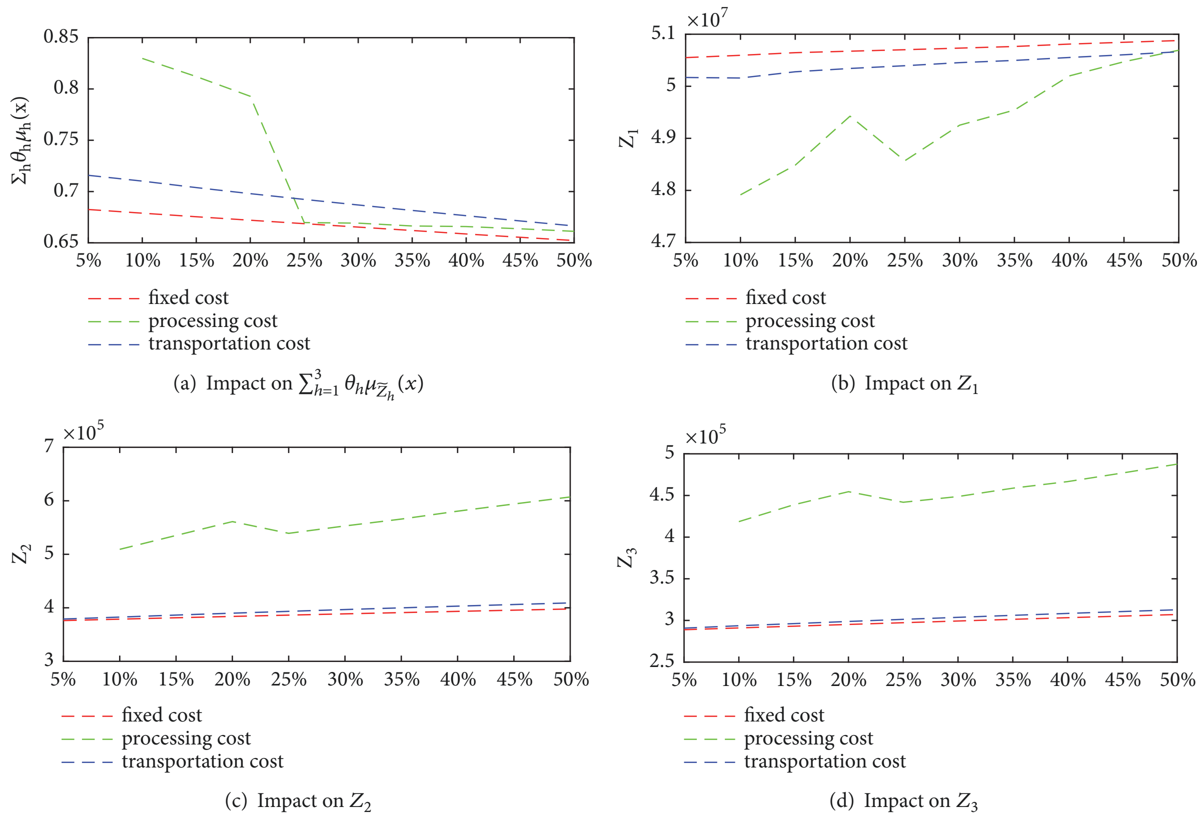


Figure 7: Sensitivity of fuzzy cost coefficients' variance.

Table 18: Impact of nonferrous components' selling price on choice of opening sites.

Open or not	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
K1	1	1	1	1	1	1	1	1	1	1
K2	0	0	0	0	0	0	0	0	0	0
K3	0	0	0	0	0	0	0	0	0	0
K4	1	0	0	0	0	0	0	0	1	0
K5	1	1	1	1	1	1	1	1	1	1
K6	0	1	1	1	1	1	1	1	0	1
L1	0	0	0	0	1	1	1	1	0	0
L2	1	1	1	1	1	1	1	0	1	1
L3	0	0	0	0	0	0	0	1	1	1
L4	1	1	1	1	0	0	0	0	0	0
L5	1	1	1	1	1	1	1	1	1	1

sets so as to reveal what are its impacts on the optimal solution.

By changing the dispersion level of the fuzzy selling prices in model (2) with a step length of 5% increment, 40 scenarios are generated, which consist of 10 different levels of the selling price of ferrous components, 10 different levels of the selling price of nonferrous components, 10 different levels of the selling price of ferrous material, and 10 different levels of the selling price of nonferrous material.

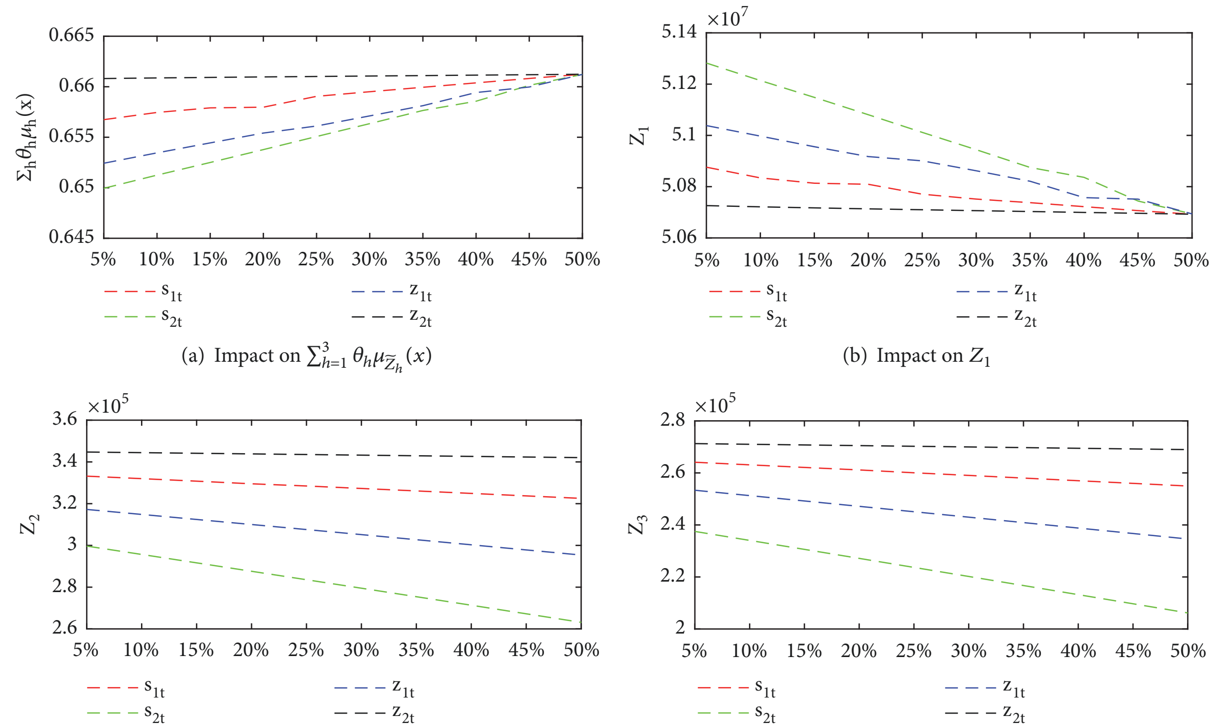
Implement Algorithm 1 to solve the corresponding models. From the results of numerical experiments, it is found that only the selling price of ferrous and nonferrous components generates serious impact on choice of opening sites. For this reason, we only present the numerical results on fuzzy selling prices of nonferrous components and ferrous materials in Tables 18 and 19, while those on the fuzzy selling prices of ferrous components and nonferrous materials are omitted. In Figure 8, we further present the impacts of their variances on $\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x)$, Z_1, Z_2, and Z_3, respectively.

From Tables 18 and 19, and Figure 8, it is easy to see that

(i) Tables 18 and 19 show that the increment in dispersion level of selling price of nonferrous components and ferrous material generates a change in choice of

Table 19: Impact of ferrous material' selling price on choice of opening sites.

Open or not	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
K1	1	1	1	1	1	1	1	1	1	1
K2	0	0	0	0	0	0	0	0	0	0
K3	0	0	0	0	0	0	0	0	0	0
K4	1	0	1	1	1	0	0	0	1	0
K5	1	1	1	1	1	1	1	1	1	1
K6	0	1	0	0	0	1	1	1	0	1
L1	0	1	0	1	0	1	1	0	1	0
L2	1	1	1	1	0	0	0	1	0	1
L3	0	1	0	1	1	1	1	1	1	1
L4	1	0	1	0	1	0	0	0	0	0
L5	1	0	1	0	1	1	1	1	1	1



(a) Impact on $\sum_{h=1}^{3} \theta_h \mu_{\tilde{Z}_h}(x)$

(b) Impact on Z_1

(c) Impact on Z_2

(d) Impact on Z_3

Figure 8: Sensitivity of selling price's variance.

opening sites for the dismantlers and shredders. In any scenario, the number of opening sites is not affected by the dispersion levels of fuzzy selling price.

(ii) Larger dispersion level leads to greater satisfaction degree $\sum_{h=1}^{3} \theta_h \mu_{\tilde{Z}_h}(x)$. From Figure 8(a), it is clear that, with increasing variances, the satisfaction degree $\sum_{h=1}^{3} \theta_h \mu_{\tilde{Z}_h}(x)$ becomes greater. The selling price of nonferrous components causes the most obvious change, followed by ferrous material, ferrous components, and nonferrous material. When the increment reaches 50%, their satisfaction degrees are the same.

(iii) From Figures 8(b), 8(c), and 8(d), an increasing selling price dispersion level causes a drop of the center value, Z_1, and the variances, Z_2 and Z_3. The contribution from the selling price of nonferrous components is greater than those from the others. When the increment reaches a threshold value (50% or so for the given scenario), the center values Z_1 are the same. Therefore, more satisfactory solutions may be obtained as the selling price variances of the nonferrous components or ferrous materials properly increase.

A comparison between Figures 7 and 8 indicates that reducing the variances of fuzzy cost coefficients is more

Table 20: Impact of capacity's ST in dismantlers.

Open or not	5%-10%	15%	20%-35%	40%	45%-90%	95%	100%
K1	1	1	1	1	1	1	1
K2	0	0	0	0	0	0	0
K3	0	0	0	0	0	0	0
K4	0	1	0	1	0	1	0
K5	1	1	1	1	1	1	1
K6	1	0	1	0	1	0	1

Table 21: Impact of capacity's ST in shredders.

Open or not	5%	10%	15%-60%	65%	70%-95%	100%
K1	1	1	1	1	1	1
K2	0	0	0	0	0	0
K3	0	0	0	0	0	0
K4	0	1	0	1	0	1
K5	1	1	1	1	1	1
K6	1	0	1	0	1	0

Table 22: Impact of capacity's ST in landfill.

Open or not	5%-40%	45%-55%	60%	65%	70%-75%	80%	85%-90%	95%-100%
K1	1	1	1	1	1	1	1	1
K2	0	0	0	0	0	0	0	0
K3	0	0	0	0	0	0	0	0
K4	0	1	0	1	0	1	0	1
K5	1	1	1	1	1	1	1	1
K6	1	0	1	0	1	0	1	0

Table 23: Impact of demand's ST in secondary markets for ferrous components.

Open or not	5%-25%	30%-70%	75%	80%-85%	90%-100%
K1	1	1	1	1	1
K2	0	0	0	0	0
K3	0	0	0	0	0
K4	0	1	0	1	0
K5	1	1	1	1	1
K6	1	0	1	0	1

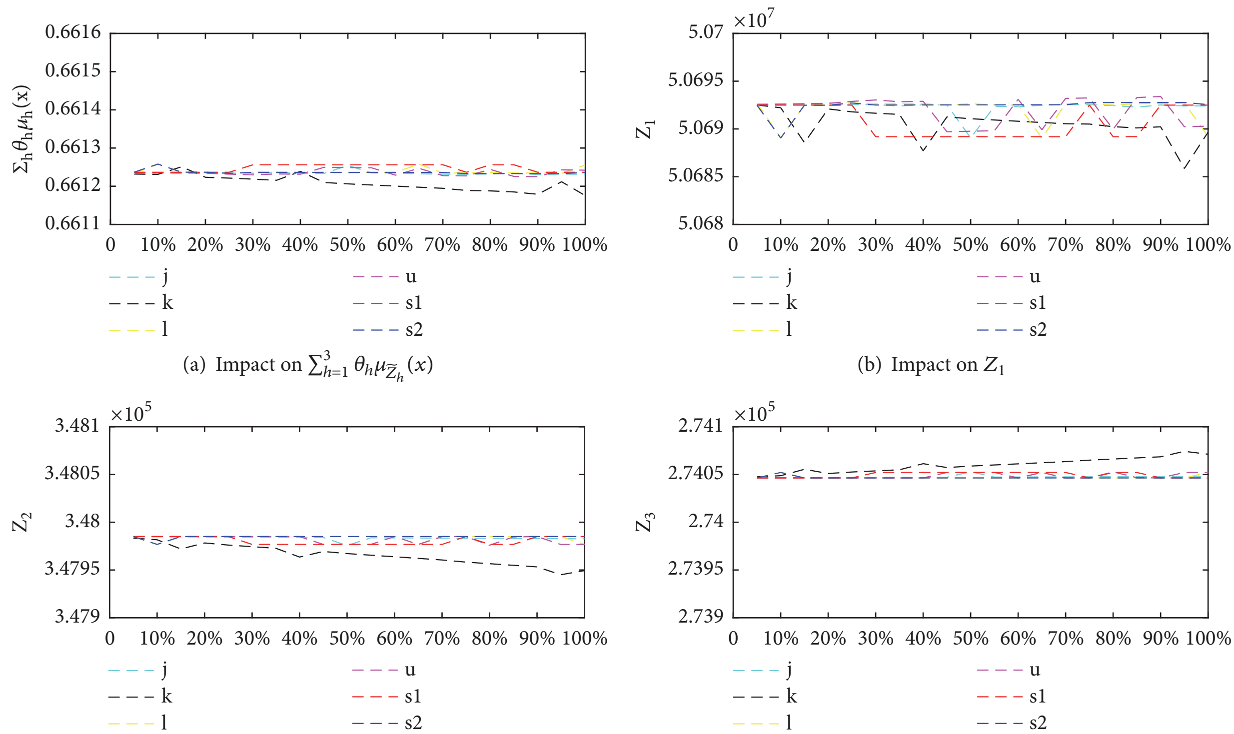
effective on increment of satisfaction degree and reduction of expected total cost than that by increasing the variances of fuzzy selling prices. Thus, instead of increasing the selling prices, decision-makers should pay more attention to reduction of the processing costs, the transportation costs, or the fixed opening costs.

5.3. Impacts of Randomness. In construction of model, we have assumed that the capacities and demands in model (2) are random. Thus, one of our concerns is to test the impact of their ST on the optimal solution.

By changing the value of ST with a step length of 5% increment, 120 scenarios are generated. Then, we implement Algorithm 1 to solve the corresponding models. From the results of numerical experiments, it is found that the capacity's ST in dismantlers, shredders, and landfills and the demand's ST in the secondary markets for ferrous components have impacts on the choice of opening sites for the dismantlers, while none of the ST generates serious impact on the choice of opening sites for the shredders. For this reason, we only present the numerical results that cause impacts on the choice of opening sites in Tables 20, 21, 22, and 23, while the other scenarios are omitted. In Figure 9, we present the impacts of ST on $\sum_{h=1}^{3}\theta_h\mu_{\widetilde{Z}_h}(x)$, Z_1, Z_2, and Z_3, respectively.

From Tables 20, 21, 22, and 23 and Figure 9, it is concluded that

(i) The increment of ST causes two kinds of schemes for choosing the opening sites of dismantlers. In our scenario analysis, we should open Dismantlers 1, 5, and 6 or open Dismantlers 1, 4, and 5 (see Tables 20,



(a) Impact on $\sum_{h=1}^{3} \theta_h \mu_{\widetilde{Z}_h}(x)$

(b) Impact on Z_1

(c) Impact on Z_2

(d) Impact on Z_3

FIGURE 9: Sensitivity of standard deviation.

21, 22, and 23). In any scenario, the number of opening sites is not affected by ST.

(ii) An increasing ST has almost the same impact on the satisfaction degree, i.e., $\sum_{h=1}^{3} \theta_h \mu_{\widetilde{Z}_h}(x)$, but the impact is extremely small (see Figure 9(a)). Comparatively speaking, the impact of the capacity's ST in dismantlers is obvious than those in the other nodes.

(iii) The center value Z_1 and the deviations Z_2 and Z_3 are affected by the increasing ST (see Figures 9(b), 9(c), and 9(d)). However, compared with Figures 7 and 8, it is seen that the impacts caused by ST are quite smaller than that caused by that of cost coefficients or selling prices on the center value Z_1 and the deviations Z_2 and Z_3. That is to say, uncertainty of costs may be more critical to the decision-making than that of demand and capacity if the demands or the processing capacities are large enough, as shown in the conducted case study.

6. Conclusions and Directions of Future Research

In this paper, we have built an optimization model with fuzzy and stochastic parameters for the production planning problems of recycling ELVs under polymorphic uncertain environment by taking into account a number of uncertain parameters.

For this complicated PUOM, a so-called chance-constrained and multiobjective programming method has been proposed to find a compromising solution for an optimal plan of recycling ELVs. Scenario analysis and sensitivity analysis have indicated that the developed algorithm is efficient and can provide a number of valuable managerial insights from the PUOM model.

Specifically, main results in this paper include the following:

(1) The proposed model and the developed algorithm in this paper have provided an efficient quantitative method to find a compromising (optimal) policy for the practical ELV recovery management problem in an uncertain environment. In particular, the proposed method can help decision-maker to choose an optimal number of opening recovery sites, optimal transportation quantities in the ELV recovery network.

(2) Faced with uncertainty in ELV recovery management, decision-makers could choose a relatively greater compensation coefficient to make a greater least satisfaction degree as they apply the presented model and algorithm in this paper into the practical decision-making. Moreover, by our model and algorithm, some critical threshold values being associated with an optimal recovery policy can be found out in the case that the practical recovery environment changes.

(3) Variance of fuzzy costs or selling prices may lead to a change of opening sites for the dismantlers or shredders. Reducing the variance of processing costs or increasing the variance of selling prices are two effective methods to make a larger satisfaction degree for the ELV recovery system. Reduction of the costs such as the processing costs and the transportation costs generate more significant impacts on the optimal recycling policy than the change of the component selling prices in the secondary markets.

(4) Small changes of demand and capacity would not generate serious impact on the optimal recovery policies in the case that the demands or the processing capacities are large enough. It is suggested that adopting advanced processing technology and machinery equipment is the most important measure to improve the ELV recovery efficiency in this case. That is to say, fuzziness of costs may be more critical to the decision-making than randomness of demand and capacity.

For future research, the problem can be extended to a closed-loop green supply chain system. Especially, if the deterministic equivalent formulation of the original model is nonsmooth or is involved with hundreds of integer variables (the number of dismantlers and shredders), then development of heuristic algorithms is necessary since it is an NP-hard problem.

Additionally, if one considers the games between governments and recycling enterprises, it is worth further studying new models from the perspective of game theory, rather than from the centralized decision-making mode in this paper. Particularly, in the case that the collection centers and the processing centers of ELVs seek to maximize their profits as different agents, it is necessary to construct a new model in decentralized decision-making mode.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

We declare that all the authors have no any conflict of interest about submission and publication of this paper.

Authors' Contributions

Zhong Wan and Jing Zhang conceived and designed the research plan; Jingjing Liu and Zhang Wan performed the mathematical modelling, numerical analysis and wrote the paper.

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